ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL OF SCIENCE ENGINEERING AND TECHNOLOGY

Department of Informatics

Architectural Design Computing Programme

and

UNIVERSIDADE DE LISBOA ★ FACULDADE DE ARQUITETURA

Doutoramento em Arquitetura

Especialidade em Desenho e Computação

AN UNINTERRUPTED URBAN WALK: 3D ANALYSIS METHODS FOR SUPPORTING THE DESIGN OF WALKABLE STREETS

Ph.D. THESIS

Elif ENSARİ SUCUOĞLU

Thesis Advisor: Prof. Dr. Mine ÖZKAR

Thesis Co-Advisor: Assist. Prof. Dr. José Nuno BEIRÃO

JANUARY 2020

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<u>İSTANBUL TEKNİK ÜNİVERSİTESİ ★ FEN BİLİMLERİ ENSTİTÜSÜ</u>

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Tasarım ve Bilgisayar Uzmanlığı

KENTTE KESİNTİSİZ BİR YÜRÜYÜŞ: YÜRÜNEBİLİR SOKAKLARIN TASARIM DESTEĞİ İÇİN 3B ANALİZ YÖNTEMLERİ

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OCAK 2020

Elif Ensari Sucuoğlu, a Ph.D. Student of İTU Graduate School of Science Engineering and Technology with student ID 523142010, and Universidade de Lisboa Faculdade de Arquitetura with student ID 20173041, successfully defended the dissertation entitled "An Uninterrupted Urban Walk: 3D Analysis Methods for Supporting the Design of Walkable Streets", which she prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

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To Can and Levent,

FOREWORD

Firstly, I would like to express my deep gratitude to my advisor Mine ÖZKAR, an admirable mentor and scholar, whom I am grateful to have met and worked with. Our conversations not only shaped this thesis, but have further inspired me to pursue a research career. I appreciate her friendly advice and aspire to become a meticulous researcher; a kind and curious teacher like her.

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January 2020 Elif ENSARİ SUCUOĞLU

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ABBREVIATIONS

ANSS : Average Number of Street Sides
API : Application Programming Interface
BIM : Building Information Modeling
CAD : Computer Aided Design
CIM : City Information Model
COV : Coefficient of Variation
CS : Convex Space
CV : Convex-Void
FAR : Floor Area Ratio
GAM : Generalized Additive Model (GAM)
GIS : Geographic Information Systems
GPS : Global Positioning System
GSM : Global System for Mobile Communication
GSV : Google Street View
IQR : Inter Quartile Range
LBSM : Location Based Social Media
LBSN : Location Based Social Network
LSS : Location Sharing Services
LIDAR : Light Detection and Ranging
MARS : Multivariate Adaptive Regression Splines
NSS : Number of Street Sides
RMSE : Root Mean Square Error
STV : Street-Void
SV : Solid-Void
WAV : Weighted Average Value

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AN UNINTERRUPTED URBAN WALK: 3D ANALYSIS METHODS FOR SUPPORTING THE DESIGN OF WALKABLE STREETS

SUMMARY

Today, rapidly growing urban populations both contribute to global crises such as pollution, climate change, diminishing natural resources, social conflicts and mass migrations and face the consequences. The built environment, its planning and design are critical in organizing urban life so that we pollute less, distribute our resources fairly, strengthen social and communal ties and thrive economically. Designing our cities to support walking as a means of transport contributes in these goals through facilitating pollution free and democratic access to urban resources, supporting local economies and enlivening the street. While research on walkability of the built environment is decades old now, we have more up-to-date, accurate and large-scale urban data than ever and our developing tools make it possible to feed this data into design and management processes to create and sustain more walkable environments.

This dissertation argues for the necessity of a street-scale, 3d analysis method to inform flexible urban design solutions based on rapidly updatable and remotely accessible urban data obtained without the necessity of on-site surveys, proposing a semi-automated workflow to fill this gap in existing literature. The workflow combines a 3d neighborhood model in a visual programming environment, GIS and custom codes, utilizing a morphological analysis model named Convex and Solid-Voids, together with web scraping and image recognition techniques. A 3d street space unit "Street-Void" is presented within the Convex and Solid-Void model in which all gathered data is aggregated for analysis. Specific indicators are identified to more accurately assess street spaces, first by distinguishing between and then quantitatively evaluating street-like and square-like, residential and mixed-use streets. Based on the findings from the application of the workflow to four neighborhoods studied in the cities of Istanbul and Lisbon and a classification of street spaces using the proposed attributes, a set of recommendations are presented, with value ranges applicable to specific street typologies. These recommendations are formulated so that they can be applied holistically or in a fragmented way at different stages of planning and urban improvement scenarios with their projected impact grouped under direct/physical or indirect/perceptual.

The dissertation contributes to walkability research by proposing a micro-scale, 3d and remotely applicable walkability analysis workflow as well as distinguishing between indicators to be applied to street spaces of different shapes and uses. It furthers the computational urban analysis model Convex and Solid-Voids by presenting its first-time application to the tangible urban problem of walkability. It also demonstrates the integration of remotely accessible data sources including street view images from an online map platform and location based social network data to the quantitative evaluation of urban street spaces. With urban planning and design recommendations, it demonstrates the practical application of the findings to urban improvement scenarios. The study is envisioned to be developed by future work through multiplying

the contexts that are studied, improving the quality and accuracy of urban data utilized, increasing the level of detail captured by the morphological analysis model and applying the analysis to other urban phenomena other than walkability.

Keywords: Measuring walkability, Urban morphology, Urban data, 3D Urban analysis, Sustainable mobility, GIS.

KENTTE KESİNTİSİZ BİR YÜRÜYÜŞ: YÜRÜNEBİLİR SOKAKLARIN TASARIM DESTEĞİ İÇİN 3B ANALİZ YÖNTEMLERİ

ÖZET

Dünyada hızla büyüyen kentsel nüfus, çevre kirliliği, iklim değişikliği, yok olan kaynaklar, sosyal çatışma ve toplu göçler gibi global ölçekteki krizlere hem sebep olmakta hem de bu krizlerle yüzleşmek durumunda kalmaktadır. Yapılı çevrenin planlanması ve tasarımı, kentsel yaşamı organize ederken daha az kirlilik yaratmak, kaynakları demokratik olarak dağıtmak, sosyal ve toplumsal bağları güçlendirmek ve ekonomik kalkınmayı desteklemek açısından kritik önem taşımaktadır. Şehirlerimizi, yürümeyi bir ulaşım biçimi olarak kullanmayı mümkün kılacak şekilde tasarlamak, kirlilik yaratmadan herkesin kaynaklara ulaşımını sağlayarak, yerel ekonomiyi destekleyerek ve sokak hayatını canlandırarak bu yönde atılan adımlara katkıda bulunmaktadır. Yürünebilirliğe dair araştırmalar yıllardır süregelirken, hiçbir zaman olmadığı kadar güncel, büyük ölçekte ve kesinlikte kentsel veriye erişimimiz var ve gelişen teknolojilerimiz bu veri ile yürünebilir kentler tasarlamaya ve yönetmeye yönelik süreçleri desteklemeyi mümkün kılmakta.

Bu doktora tezi, sokak ölçeğinde, üç boyutlu ve esnek kentsel tasarım süreçlerini bilgilendirecek, hızla güncellenebilir ve uzaktan erişilebilir kentsel veriye dayalı, dolayısıyla arazi çalışmalarını gerektirmeyecek bir analiz metodunun gerekliliğini öne sürmekte ve literatürdeki bu boşluğu dolduran, yarı-otomatik bir iş akışı sunmaktadır. Bu iş akışının, mevcut literatürdeki yürünebilirlik araştırmaları ile kentsel tasarım süreçleri arasındaki kopukluğu gidermesi öngörülmektedir. Bu kopukluğun, tasarım ve planlama süreçlerinde ekonomik kriterlerin öncelikli olması ile bu süreçlere yönelik farklı aşamalarda, parçalı ve bütüncül olarak uygulanabilir hızlı ve pratik değerlendirme yöntemlerinin eksikliğinden kaynaklandığı öne sürülmektedir. Ayrıca halihazırda bulunan yürünebilirlik değerlendirme yöntemleri, tez çalışmasının odaklandığı sokak ölçeği detayında bir ölçümü uzaktan toplanabilen kentsel veri üzerinden yapamamakta, zaman ve maddi açıdan yük teşkil eden yerinde ölçümlere ihtiyaç duymaktadır. Sunulan iş akışının bu eksikliklere cevap vermesi hedeflenmektedir. İş akışı, görsel bir programlama ortamında, üç boyutlu bir mahalle modelini coğrafi bilgi sistemleri (CBS) ve özel kodlarla bir araya getirmekte; Dışbükey ve Dolu-Boş Hacim Modelleri (Convex and Solid-Void Models) adında bir morfolojik analiz modelini web kazıma ve makine görüşü teknikleri ile birlikte kullanmaktadır.

Bu tez, yürünebilirlik araştırmalarına, mikro ölçekli, üç boyutlu ve uzaktan uygulanabilir bir yürünebilirlik analizi iş akışı ile farklı biçimli ve kullanımlı sokak mekanlarına özel yürünebilirlik göstergeleri ve değer aralıkları önererek katkıda bulunmaktadır. Çalışma, Dışbükey ve Dolu-Boş Hacim analiz modellerini ilk defa somut bir kentsel problemin çözümüne yönelik olarak yürünebilirliğe uygulayarak tasarımda bilişim alanına katkı sağlamaktadır. Ek olarak, uzaktan erişilebilir veri kaynaklarının kentsel mekânın sayısal analizinde kullanımına entegre edilmesine dair yenilikçi bir örnek teşkil etmektedir. Çalışmada kullanılan bu tür kaynaklar çevrimiçi

haritaların sokak görüntüsü (street view) platformları ve lokasyon bazlı sosyal ağlardır. Ancak kullanılan iş akışı, bu tür kaynakların ileriki çalışmalarla çeşitlendirilerek yönteme entegre edilmesine izin vermektedir. Bu, iş akışında CBS'nin üç boyutlu mekânsal modeller ve programlama araçlarıyla bir arada kullanımı sayesinde mümkündür. Mekânsal elemanların, semantik bilgi ile veri tabanları üzerinden ilişkilendiği bu ortamlar, veri tabanına işlenebilen her türlü verinin kullanımına izin vermektedir. Bu sayede mekâna dair edinilen çok çeşitli veri, veri tabanları üzerinden mekânsal analize dahil edilebilmekte ve üretken tasarım süreçlerini besleyebilmektedir. Ayrıca çalışma, sunduğu kentsel tasarım ve planlama önerileri ile, bulguların gerçek hayatta kentsel rehabilitasyon projelerinde kullanılmasına yönelik pratik bir kaynak niteliği taşımaktadır.

Dışbükey ve Dolu-Boş Hacim Modelleri dahilinde üç boyutlu bir sokak mekân birimi olan 'Sokak-Boşluk' (Street-Void) geliştirilmiştir. Bu birim, kentsel mekânın analizinde elde edilen tüm verinin bir araya getirilmesi ve değerlendirilmesinde kullanılabilmektedir. Buna ek olarak, öncelikle sokak veya meydan biçimli ve konut veya karma kullanımlı sokak mekanlarını ayırt edecek, sonra da bu özelliklere bağlı olarak daha doğru bir sayısal değerlendirmeyi mümkün kılacak yürünebilirlik göstergeleri belirlenmiştir. İş akışının İstanbul ve Lizbon'da dört farklı mahalleye uygulanması ve buralardaki sokak mekanlarının önerilen göstergeler üzerinden sınıflandırılması ile elde edilen değer aralıkları ile kentsel tasarım önerileri sunulmaktadır. Bu öneriler, farklı sokak tipolojilerine uygun olacak şekilde, bir kentsel mekâna bütüncül veya parçalı biçimde, farklı planlama ve tasarım aşamalarında uygulanmayı mümkün kılmak üzere organize edilmiştir. Bu tavsiyelerin öngörülen etkileri direk/fiziksel ve dolaylı/algısal olarak gruplanmıştır. Literatürde bulunan mevcut yürünebilirlik ölçüm metotları, sadece sokakların yürünebilirliklerinin ölçümüne yöneliktir ve bu çalışmada önerilen, sokak mekanlarının özelliklerine göre farklılaşan gösterge ve değer aralıkları kullanımı da literatüre yenilikçi bir katkıdır.

Tez metninin giriş bölümünde, yapılan çalışmanın amacı, literatürde öngörülen yeri ve önemi, yöntemi ve sonuçlarına dair bir tanıtım yapılmıştır.

İkinci bölüm tezin cevaplamayı amaçladığı sorular ve bunlar üzerine kurulan hipotezi sunmaktadır. Bu sorular sırasıyla şöyle sıralanabilir. Yürünebilirlik kriterleri nasıl mahalle ölçeğinde kentsel tasarım süreçlerine dahil edilebilir? Yürünebilirliğin değerlendirilmesi ve tasarım karar süreçlerinin bu bilgi ile en etkili şekilde beslenebilmesi için kentsel yapılı çevrenin hangi özellikleri dikkate alınmalıdır? Oldukça karmaşık ve değişken yapıda olan kentsel yapılı çevrenin yürünebilirliğini, mahalle ölçeğinde, en etkili şekilde nasıl değerlendirebiliriz?

Tez metninin üçüncü bölümü literatürdeki insan odaklı kentsel tasarım, yürünebilirlik ölçüm çalışmaları ve kentsel ölçeğe yönelik geliştirilen algoritmik tasarım araçlarını incelemektedir.

Dördüncü bölümde araştırmanın yöntemi ve yukarıda tanıtılan iş akışının çalışma prensibi detaylı biçimde anlatılmaktadır. Bu bölümde, yürünebilirlik ölçümü için geliştirilen sayısal göstergelerin seçim süreci de açıklanmıştır. Bu göstergelerin 'karakter özellikleri' (characteristics) olarak gruplandığı üst başlıklar; yoğunluk (density), çeşitlilik (diversity), bağlantısallık (connectivity), insan ölçeği (human scale), karmaşıklık (complexity), çevrelenmişlik (enclosure), biçim (shape), eğim (inclination), geçirgenlik (permability) ve altyapı (infrastructure) şeklinde sıralanmıştır. Bu karakter özellikleri ve altında gruplanan göstergeler çalışmanın ileri aşamalarında elenerek indirgenmiştir.

Beşinci bölümde yöntemin geliştirilmesinde kullanılan örnek mahalle uygulamaları, mahallelerin seçim kriterleri, değerlendirmede kullanılan yürünebilirlik göstergelerinin sayısal veriler üzerinden yorumlanması ve sayısal bulguların ilk analizleri yapılmıştır.

Altıncı bölümde istatistiksel yöntemlerle sosyal medya ve sokak görüntüsü analiz sonuçlarının yürünebilirlik göstergeleri olarak kullanılabilirliği test edilmiş ve kullanılan göstergeler üzerinden incelenen sokak mekanları gruplanmış, sokak tipolojileri elde edilmiştir. Elde edilen tipolojilerin özellikleriyle ölçülen göstergelerin sayısal sonuçları karşılaştırılmış, bu karşılaştırmalar üzerinden göstergeler değerlendirilmiş ve elemeye tabi tutulmuştur.

Yedinci bölüm, biçim ve kullanım amacına bağlı olarak sokak mekanlarının tekrar gruplanması ve gösterge sonuçlarının bu gruplar için kıyaslanarak incelenmesini içerir. İnceleme sonuçları üzerinden farklı sokaklar için uygulamaya yönelik değer aralıkları belirlenmiş ve tüm bulgular tasarım ve planlama süreçlerine yönelik bir rehber haline getirilmiştir.

Sekizinci bölüm tezin tüm çıktısını; literatüre ve tasarım ile planlama süreçlerine katkısını, kısıtlamaları, tezin ilk adımını teşkil ettiği ve gelecekte yapılması öngörülen çalışmaları özetlemektedir.

Önerilen yürünebilirlik ölçüm metodu ve beraberinde sunulan kentsel planlama ve tasarıma yönelik tavsiyeler, bu tezde geliştirilmiş biçimleriyle, yerel ve merkezi belediyeler ve özel müteahhitler ile bunlarla çalışacak plancı ve tasarımcılara yönelik danışmanlık hizmetleri kapsamında kullanılabilir niteliktedir. Öngörülen gelecek çalışmalarla, sunulan iş akışının, plancı ve tasarımcıların kullanımına yönelik bir set araç haline getirilmesi ve incelenecek farklı sokak tipleriyle, Türkiye ve Portekiz bağlamları dışında da kullanılabilmesi planlanmaktadır.

Projenin geliştirilmesine yönelik öngörülen bazı çalışmalar, örnek olarak kullanılan kentsel bağlamların çeşitlendirilmesi, kentsel verinin hassasiyetinin ve kesinliğinin arttırılması, kullanılan morfolojik analizin değerlendirdiği detay seviyesinin yükseltilmesi ve kullanılan mekânsal analiz yönteminin yürünebilirlik dışındaki kentsel konulara da uygulanmasını içerir. Mevcut çalışmada kullanılan İstanbul ve Lizbon şehirlerindeki Kadıköy, Hasanpaşa, Chiado ve Ajuda mahalleleri, yapısal benzerlikleri açısından tutarlı ve aynı zamanda yeterli çeşitlilikte sokak tipolojisinin değerlendirilmesine imkân vermiştir. Özellikle ölçek ve kullanım çeşitliliği bakımından benzer yapıda olan bu mahalleler, kullanılan göstergelerle sınıflandırıldıklarında 6 farklı sokak tipolojisi elde edilmiştir. Ancak iş akışı ölçek, biçim ve kullanım açısından daha farklı örneklere uygulanarak bu tipolojiler çeşitlendirilmelidir. Hem ilgili verinin detaylı şekilde mevcut olması hem de bahsedilen özellikler açısından çok daha çeşitli sokak mekanları barındırmaları itibari ile New York, Singapur ve Amsterdam, çalışılması düşünülen şehirlerden ilkleridir.

Anahtar kelimeler: Yürünebilirlik ölçümü, Kentsel morfoloji, Kentsel veri, 3B Kent Analizi, Sürdürülebilir ulaşım, CBS.

A CAMINHADA URBANA ININTERRUPTA: MÉTODOS DE ANÁLISE 3D PARA APOIAR O PROJETO DE RUAS CAMINHÁVEIS

RESUMO

Os aglomerados urbanos em rápido crescimento contribuem e enfrentam hoje, as consequências de crises globais, como a poluição, as alterações climáticas, a diminuição dos recursos naturais, conflitos sociais e migrações em massa. O planeamento e projecto do ambiente construído são essenciais para uma correcta organização da vida urbana, de modo a reduzir a poluição, distribuir recursos de maneira justa, fortalecer laços sociais e comunitários e prosperar economicamente. Projectar cidades incentivando a pedestrianização como meio de transporte constitui uma contribuição para esses objectivos, facilitando a mitigação da poluição, o acesso livre e democrático aos recursos urbanos, revitalizando as ruas e consequentemente apoiando as economias locais. Embora a investigação sobre a pedestrianização e caminhabilidade do ambiente construído já tenha décadas, temos hoje dados urbanos atualizados e ferramentas mais precisas do que nunca, que permitem uma análise detalhada dos factores que promovem a pedestrianização, podendo suportar decisões baseadas em evidências para o desenvolvimento de uma mobilidade mais sustentável. Tais ferramentas de planeamento viabilizam também uma melhor integração destes dados nos processos de projecto bem como a sua comunicação aos vários agentes participantes na decisão.

Esta dissertação defende a necessidade de um método de análise 3D à escala da rua para informar soluções flexíveis de projecto urbano baseadas em dados urbanos rapidamente actualizáveis e acessíveis remotamente, obtidos sem a necessidade de pesquisas no local. Este método preenche uma lacuna existente na literatura propondo um fluxo de trabalho semi-automático. Este fluxo de trabalho propõe-se solucionar a desconexão entre a investigação no campo da pedestrianização, as ferramentas existentes e os processos de planeamento e projecto urbano. Argumenta-se que essa desconexão resulta da priorização de preocupações financeiras nos processos de planeamento e desenho urbano e da falta de métodos de avaliação rápidos e práticos aplicáveis nas várias etapas e escalas de projecto e de um modo fragmentado ou holístico. Além disso, os métodos existentes de avaliação da caminhabilidade que avaliam contextos urbanos nestas escalas e detalhe, não são capazes de avaliar ruas através de dados urbanos acedidos remotamente, recorrendo geralmente a auditorias ou pesquisas onerosas e morosas no local. O fluxo de trabalho proposto neste estudo visa responder a esta necessidade; combina um modelo 3D de uma unidade de vizinhança desenvolvido num ambiente de programação visual, SIG e códigos personalizados, e utiliza um modelo de análise morfológica chamado *Convex* e *Solid-Void*, combinado com técnicas de *Web-scrapping* e reconhecimento de imagem.

A dissertação contribui para a investigação sobre caminhabilidade, propondo um fluxo de trabalho de análise de caminhabilidade em escala micro, em 3D, e remotamente aplicável, além de distinguir indicadores aplicáveis a ruas com diferentes formas e

usos. O método promove o modelo computacional de análise urbana, *Convex* e *Solid-Void*, apresentando a sua primeira aplicação ao problema urbano da caminhabilidade. Também demonstra a integração de fontes de dados acessíveis remotamente, incluindo imagens de *Street View* obtidas de uma plataforma de mapas *on-line* e dados de redes sociais geo-localizados, para a avaliação quantitativa dos espaços urbanos. De futuro, pretende-se desenvolver o método para permitir o acesso remoto da avaliação a várias dessas fontes de dados. Tal é possível pelo uso combinado de SIG com representações espaciais 3D e ferramentas de programação integradas no mesmo fluxo de trabalho. Estes ambientes, que facilitam a associação de elementos espaciais com informações semânticas por meio de bases de dados, possibilitam a utilização de quaisquer dados que possam ser processados em análise espacial para alimentação de processos de projecto gerativo. O resultado desta pesquisa apresenta-se na forma de recomendações de planeamento e desenho urbano e também pretende ser um recurso prático a ser usado em projectos de reabilitação urbana.

Como parte do modelo *Convex* e *Solid-Void* usado neste estudo, apresenta-se uma nova unidade espacial 3D "*Street-Void*", na qual todos os dados coletados são agregados para análise. Identificam-se indicadores específicos para avaliar com mais precisão os espaços das ruas, primeiro distinguindo entre ruas e praças e depois avaliando quantitativamente espaços semelhantes a ruas e espaços semelhantes a praças, e ainda espaços residenciais e de uso misto. Com base nos resultados da aplicação do método a quatro bairros estudados nas cidades de Istambul e Lisboa, e uma classificação das ruas usando os indicadores identificados, apresenta-se um conjunto de recomendações, que se atribuem a intervalos de valores próprios das tipologias específicas de ruas. Estas recomendações são formuladas para que possam ser aplicadas holisticamente ou de maneira fragmentada em diferentes fases de projecto ou cenários de melhoria urbana. Este estudo amplia o conhecimento sobre pedestrianização, sugerindo diferentes indicadores e faixas de valor para a avaliação de ruas, relacionando caminhabilidade com a variação das suas formas e usos.

A tese está organizada da seguinte forma. No capítulo de introdução, são apresentados brevemente os objetivos da pesquisa, a contribuição e importância para o tema, metodologia, resultados e conclusão.

No segundo capítulo, são apresentadas as questões de investigação a que a tese responde e a hipótese construída sobre essas questões. Estas questões podem ser listadas da seguinte maneira. Como podem a caminhabilidade e seus critérios serem integrados nos processos de desenho urbano (à escala do bairro)? Quais as qualidades do ambiente urbano construído que devem ser consideradas para a avaliação da caminhabilidade, para que as decisões de projecto possam ser informadas com mais eficácia? Como podemos avaliar a pedestrianização de um bairro num ambiente urbano complexo e em constante mudança?

O terceiro capítulo apresenta uma revisão da literatura no tema da pesquisa, incluindo os temas do projecto urbano centrados no ser humano, investigação existente sobre a medição da caminhabilidade e sobre ferramentas de projecto algorítmico desenvolvidas para a escala urbana e em particular para a escala do bairro.

No quarto capítulo, são explicados o método do estudo realizado e os princípios do fluxo de trabalho acima apresentados. Discute-se o processo de selecção utilizado para determinar os atributos quantitativos para a medição da caminhabilidade. As “características” sob as quais esses atributos são agrupados são a densidade, diversidade, conectividade, escala humana, complexidade, clausura (*enclosure*), forma, inclinação, permeabilidade e infraestrutura. Estas características e atributos são reduzidos posteriormente através de um processo de eliminação aos seus componentes principais.

O quinto capítulo apresenta os estudos de caso dos bairros que são utilizados no desenvolvimento do fluxo de trabalho de medição, a interpretação dos atributos de caminhabilidade face aos dados medidos e uma análise inicial desses dados quantitativos.

No sexto capítulo, o uso de dados de redes sociais e imagens *street view* como representantes de caminhabilidade são testados por métodos estatísticos e os espaços das ruas analisados são classificados com base nos atributos medidos (através de um método de *clustering*). Tipologias de rua com atributos específicos são identificadas nas várias classes (*clusters*) obtidas. Os atributos são avaliados com base na comparação de seus resultados quantitativos para cada tipologia de rua e são reduzidos através de um processo de filtragem.

O sétimo capítulo inclui uma reclassificação das ruas com base em suas formas e usos e uma avaliação das medidas dos seus atributos com base na comparação dos seus resultados para essas classes. Através dessa avaliação, diferentes intervalos de valores foram determinados para serem aplicados aos diferentes atributos das ruas, e as descobertas obtidas por este método foram convertidas num guia destinado a informar os processos de desenho e planeamento urbano.

O oitavo capítulo resume a produção geral da tese, a sua contribuição para o conhecimento, bem como para os processos de projecto e planeamento urbano. Partindo dos seus aspectos inovadores, fornece também uma visão geral dos estudos futuros que a tese pode proporcionar.

No presente desenvolvimento, o método proposto nesta tese para a medição da caminhabilidade e respectivas recomendações para os processos de projecto e planeamento podem ser utilizadas como parte de serviços de consultoria a ser prestados a municípios, consultoria particular e a profissionais de projecto e planeamento. Em estudos futuros, pretende-se tornar o fluxo de trabalho apresentado numa ferramenta que pode ser utilizada diretamente por projectistas e planeadores. Prevê-se que tais estudos sejam desenvolvidos através da multiplicação dos contextos estudados, melhorando a qualidade e a precisão dos dados urbanos utilizados, aumentando o nível de detalhe capturado pelo modelo de análise e aplicando a análise a fenómenos urbanos que não sejam somente a caminhabilidade. Devido às semelhanças dos seus ambientes construídos, os bairros utilizados no presente estudo, que são Kadikoy e Hasanpasa em Istambul e Chiado e Ajuda em Lisboa, permitiram a avaliação de um conjunto consistente de ruas, oferecendo variedade suficiente. Mais especificamente, devido às semelhanças em termos de escala e uso, quando os espaços das ruas desses bairros foram classificados com base nos atributos utilizados, revelaram-se 6 tipologias diferentes de espaços de rua. Prevê-se que essas tipologias sejam multiplicadas pela aplicação do método a contextos diferentes em termos de escala, forma e uso. Devido à disponibilidade de dados detalhados e a uma variedade de espaços nas ruas em termos dos critérios mencionados, Nova York, Singapura e Amsterdão são exemplos de cidades que poderão ser estudadas como novos casos de estudo.

Palavras-chave: Medição da caminhabilidade, Morfologia urbana, Informação urbana, Análise urbana 3D, Mobilidade sustentável, SIG

1. INTRODUCTION

1.1 What Is Walkability and Why Is It Important Now?

Some people get to start their day with a pleasant walk to the bus or the train, or all the way to work through comfortable, safe and lively streets. Others have to drive for hours due to not having alternative commuting options or access to public transportation is too burdensome where they live. In some neighborhoods, people walk to convenience stores, parks and restaurants, enjoying spontaneous conversations with their neighbors and getting acquainted with local happenings while in others, they have to take a car even to get to the nearest grocery store. Some children grow up walking or biking to school from a young age while others sit in school buses or need to be driven by their parents until they reach the legal age at which they start driving themselves. For poor populations in many developing countries, walking is not a choice, but the only means of transport even if the built environment does not provide favorable conditions for the pedestrian; basic safety, security and comfort requirements are overlooked in order to build larger roads for the few who can afford automobiles. However, where people do get to choose, their built environment has a considerable influence on whether they will walk, where to and how far they will be willing to walk. Cities with built environments that are planned and designed to encourage walking as a means of transport see a decrease in traffic congestion and air pollution as well as an improvement in the health of their residents (City of New York, 2013). Investment in urban design that supports walking pays back due to improvement in local economy and consequent increase in rents, growing job market and wealth of local populations.

Walkability is a term used to define the extent to which the built environment can accommodate a safe, comfortable and pleasant pedestrian experience. While the description of “pedestrian” generally indicates people travelling on foot, it has also been expanded to comprise people not only travelling but also standing or doing other recreational activities on foot, as well as the walking-impaired using wheelchairs (Lo, 2009). Researchers from the fields of health, urban design, transportation engineering and geography have been studying the components, means to measure and effects of walkability since the 1960s. With the advance of technology embedding computers and sensors into cities and hoards of data being generated every day, the methods and tools developed to measure walkability should become more efficient and better informed and the results be more applicable to improving cities. Furthermore, they need to be integrated in the urban design, planning and decision-making processes along with additional analysis, simulation and generative design methods. With cities growing and regenerating to accommodate the rapidly increasing urban populations, this need is more urgent than ever.

1.2 Why Another Walkability Measuring Method?

A meta-analysis conducted in 2010 (Ewing & Cervero, 2010) revealed more than two hundred academic studies on walkability, several of them presenting methods to evaluate walkability through surveys, audits and composite indices that could be replicated to assess different urban environments. With several more conducted since then, there is ample evidence that the physical built environment concerning various scales of urban planning and design, influences walking behavior, which is linked to rates of cancer, diabetes, obesity and heart disease.

Among the measuring methods and tools that have been developed and presented in these studies, some rely purely on surveys, where residents within pre-determined city regions answer questions regarding their perceptions of the local physical built environment characteristics, sufficiency of amenities within walking distance as well as their mobility behavior. Questions regarding their perceptions may be about how they would rate the quality of the sidewalks, the safety of the streets or the ease of access to destinations within their neighborhoods and those regarding their behavior may ask whether they walk to work or for exercise, how often they walk to destinations and which routes they take. Measuring methods that are concerned with larger-scale built-environment characteristics such as density, diversity and accessibility rely on 2d analysis utilizing geographic information systems (from here on GIS). Generally, their inputs are census block and building footprint areas, street network geometry, demographic and land use data. Methods that are concerned with more detailed analysis of the built environment and aim to assess these qualities more objectively, employ human auditors and sometimes utilize pictures and videos taken on site or street view imagery openly available through sources like Google Street View (Google

Maps Platform, 2019) or Bing Streetside (Microsoft, 2019). These methods count or measure features like the sidewalk quality; building heights; building façade widths, shapes and colors; window to façade area proportions; existence of vegetation and shading capacities of street trees; existence of historical buildings and landmarks; street cross-section proportions; sightlines; visibility of landscape; existence of street art, outdoor seating, planters or other street furniture. They also occasionally incorporate larger scale measures such as accessibility to amenities and public transportation. While larger scale measures are generally computed using GIS and are easy to assess objectively, smaller scale streetscape evaluations work in higher detail, assess 3d characteristics, and require information regarding the built environment collected through traditional audits which are prone to human error, and consume time and money.

This research is interested in small scale, fine grained evaluation of streetscapes for walkability, fueled by the motivation to inform urban design decisions in neighborhood-level improvement, regeneration or growth scenarios. Even though larger scale built environment qualities concerning walkability were found to be more important than local, micro-scale factors in terms of their influence on walkability (Cervero, 1993; Ewing, Hajrasouliha, Neckerman, Purciel-Hill, & Greene, 2016; Kim, Park, & Lee, 2014), local and micro-scale built environment characteristics and phenomena modifiable through municipal level interventions were found to be easier and faster to improve and therefore highly effective and necessary to investigate for walkability research (Carlson, Aytur, Gardner, & Rogers, 2015; Learnihan, Van Niel, Giles-Corti, & Knuiman, 2011; Rodríguez, Aytur, Forsyth, Oakes, & Clifton, 2008).

At this time when planning and design tools allow for easier, faster and more accurate automation of several tasks through analysis, simulation and generative design techniques, walkability evaluation should also be automated as much as possible. This will not only help cut down financial and time requirements for assessment but will also allow for more objective results. Moreover, automated evaluations are easier to combine with data sources that are frequently updateable through similarly automated methods, and their output can feed into generative design tools to form integrated design workflows. Additionally, they can be applied remotely to sites that are inaccessible such as those in conflict zones. What is standing in the way of automating the smaller scale walkability analysis methods is the difficulty to collect accurate data regarding the built environment as well as to keep this data updated in spite of the rapidly changing nature of the cities. The assessment of urban morphology and the use of big data are investigated within this research to formulate an answer to this problem.

Morphology is seen as an evidence of several phenomena also related with the urban environment (Moudon, 1997). From a perspective seeking physical, measurable streetscape attributes that influence the pedestrian experience, it can present indicators to measure several walkability related attributes. Studies have utilized morphological measures for classification of neighborhoods (Oliveira & Medeiros, 2016) and housing typologies (Pont & Haupt, 2010) and morphological measures also appear in many walkability indices; however, a detailed and rigorous morphological analysis have not been operationalized to measure walkability related characteristics and as the primary indicator of walkability before.

Data sources such as location based social media (from here on LBSM), location sharing services (LSS) and mapping services providing street view imagery are already being utilized to directly infer walkability levels (Quercia, Aiello, Schifanella, & Davies, 2015) or collect information on the streetscape attributes for measuring walkability (L. Yin, 2017). Even when deciphered manually, using this data to calculate walkability indices save time and money, however when combined with machine learning algorithms such as those that are used for image processing, they become even more valuable for evaluations. These algorithms can automate the identification of streetscape elements such as greenery and water (Maharana & Nsoesie, 2018), trees (Branson et al., 2018), visual enclosure (L. Yin & Wang, 2016), sidewalk quality (Abbott, Deshowitz, Murray, & Larson, 2018) or various façade qualities (Goodfellow, Bulatov, Ibarz, Arnoud, & Shet, 2013). Based on street view images, they can count people (L. Yin, Cheng, Wang, & Shao, 2015) and be trained to infer further information such as demographic data, voting patterns (Gebru et al., 2017) or how they would be perceived by human evaluators in terms of qualities such as how lively, beautiful, wealthy, safe, depressing or boring a street looks (Dubey, Naik, Parikh, Raskar, & Hidalgo, 2016). Openly available satellite images are also utilized to detect urban phenomena in combination with machine learning algorithms but are harder to assess for detailed streetscape information due to low resolution. To summarize, openly available images from satellites, street view services or social media platforms combined with image processing algorithms hold the potential to replace street audits in walkability research.

The aim of this thesis is to identify and operationalize a reduced set of remotely accessible morphological and streetscape urban built environment attributes that can be used to measure walkability with results capable of guiding urban design decisions in neighborhood and street-level design interventions. A semi-automated evaluation workflow developed through this research which incorporates geographic information systems (GIS) maps, parametric 3d models and big data will be presented. This workflow is envisioned to be better integrated into urban design processes, possibly through a set of plugins to be developed for existing design tools through future research.

1.3 Outline of Thesis

The following chapter lays out the problems this thesis takes on to address. Firstly, the gap between walkability research and application of its defined principles to urban design is investigated highlighting the need for financial incentives. Secondly the scale of walkability analysis methods is explored and significance of neighborhood and street-scale analysis is laid out along with difficulties in its automation. Thirdly, morphological attributes are nominated as a means to efficiently measure street and neighborhood-scale walkability. Finally, computational methods and tools are studied together with a presentation of a conceptual urban design support model and the walkability evaluation workflow that this thesis aims to generate.

The third chapter is a literature review on the concept of walkability and its existing measuring methods; various indicators currently utilized and morphological attributes of the urban built environment relevant with walkability as well as parametric design tools, GIS, city information modeling and big data that this study utilizes and sees as inevitable parts of a more holistic urban design framework.

The fourth chapter describes the methodology followed. The core of the methodology incorporates an initial identification of neighborhood and street-level urban built environment characteristics correlated with walkability in literature which can be measured through 3d morphology; the extension of Convex and Solid-Void models (Beirão, Chaszar, & Čavić, 2015; Beirão, Chazsar, & Čavić, 2014; Čavić, Sileryte, &

Beirão, 2017; Sileryte, Čavić, & Beirão, 2017) which comprise the application of a previously developed morphological analysis method on four case studies; further analysis of streetscape attributes in the case studies through image processing street view imagery; and the analysis and refinement of results. This is followed with the inference of recommendations based on value ranges of morphological indicators pertaining to different levels of walkability.

The fifth chapter presents the case studies carried out in two neighborhoods of Istanbul: Caferağa and Hasanpaşa, and two neighborhoods in Lisbon: Chiado and Ajuda. Based on an initial analysis of physical and demographic features as well as quantitative social media data, Caferağa and Chiado were selected as examples of walkable neighborhoods whereas Hasanpaşa and Ajuda were selected as examples that are not walkable. Results of Convex and Solid-Void model analysis combined with street view feature analysis of four neighborhoods are shown and compared for neighborhoods for a preliminary interpretation of how well the attribute measures perform. Measured attributes are grouped under key characteristics based on literature.

Chapter six lays out the results of predictive statistical analysis and clustering applied to the morphological and streetscape analysis findings. These are compared with the initially defined characteristics inferred from literature and are used to refine them.

Chapter seven compiles a set of recommendations for urban planners and designers to support their decision making in planning and design processes based on the findings. Whether they create impact on the physical or perceptual qualities influencing walkability are also presented. These recommendations are translations of morphological measures to real-life urban improvement and growth scenarios.

Chapter eight presents a conclusion, elaborating on morphological indicators and the workflow developed for their automated evaluation, discussion of limitations and projections for further development of the workflow in future study.

1.4 Contributions

The research process and findings are expected to firstly contribute in walkability literature through the introduction of neighborhood and street-level walkability indicators based primarily on the morphology of the built environment. A practically applicable set of indicators are defined which is intended to reduce the costs of audits, modeling and assessment traditionally used for measuring neighborhood level walkability.

Secondly, a semi-automated method for analyzing walkability combining a parametric 3d model with GIS is introduced into the analytical urban design support methods. Along with the development of the previously introduced Convex and Solid-Void models (Beirão et al., 2015, 2014; Čavić et al., 2017; Sileryte et al., 2017) to facilitate the measuring of walkability, the use of street view images analyzed by an image recognition algorithm is tested for the identification and location of streetscape features relevant for walkability.

Thirdly LBSM and LSS data is used to assess street activity and the representativeness of social media is investigated in four different contexts from two cities with various similar and diverse characteristics. Whether this can be utilized as a replacement for field audits to determine urban activity and validation of walkability measures is tested.

Additionally, a classification based on the morphological attribute of street space shape and land use is proposed as a preliminary step in evaluating walkability. This is presented as a means to distinguish different morphological attributes that are applicable to street spaces with different characteristics as well as different quantitative ranges based on which to assess them.

Finally, a set of recommendations based on the findings are presented to support the design processes of built environments towards better walkability conditions. These recommendations are aimed to contribute in urban design decision making at different levels of intervention.

2. PROBLEM STATEMENT

This thesis addresses the gap between the walkability research and the design practices that shape the urban environment, aiming to respond to the problem of impracticalities and labor-intensive processes in evaluating street and neighborhood-level walkability. The issues of scale of evaluation closely related with the municipal design and planning capacities as well as the data collection methods usually adopted in walkability research are challenged. The difficulties in dealing with complex and fluctuating nature of urban environments are addressed through exploring semi-automated and algorithmic methods for both evaluation and data collecting processes. Finally, the question of how to select the most practically measurable and effectively applicable indicators within the vast set of walkability indicators is investigated.

The research responds to these problems by proposing a semi-automated workflow to analyze a concise set of 3d morphological properties of urban streets. These properties are selected so that they define a level of affordance of the built environment for walkability, accounting for several of the commonly utilized walkability indicators and therefore optimizing the evaluation process. Data required for the analysis is obtained through free, publicly available, geographically extensive and up-to date data sources and partially using automated queries to online platforms. The final output is an analysis workflow and recommendations aimed to support local municipality level urban improvement decisions for walkability.

2.1 The Disconnect of Walkability Research with Urban Design Decisions

Despite extensive studies proving the benefits of walkable urban environments for public health, local economy and urban sustainability; there is a gap between research and contemporary urban planning and design practices. Several studies address the relationship between the built environment qualities and the walking behavior of urban residents (Badland & Schofield, 2005; Frank et al., 2010; Hooper, Knuiman, Bull, Jones, & Giles-Corti, 2015; Saelens & Handy, 2008; Sarkar et al., 2015), yet merely a handful of first world countries adopt this knowledge in their urban planning policies.

Playing a leading role in the shaping of urban environments for cities with rapidly growing populations, land use and transportation planning policies often end up fueling sprawl through land speculation, decongestion strategies and rapid development of low cost housing outside the centers in developing countries (Cervero, 2013). To promote walkable urban development in the city and regional scale, criteria such as density, diversity and connectivity of public transportation networks need to be prioritized in strategic urban plans and be incorporated into lower level municipal plans. In the neighborhood and street-level, local municipalities are the executive authorities who have control over the design, construction and maintenance of built environments and urban design guides prepared by municipalities or planning authorities can be regarded as the main documents of reference to understand the stance of urban design policies regarding the walkability of the built environment. In this scale, considering the upper hand of municipalities and the numerous stake holders involved in the planning of the urban realm, a deficit in relevant legislation makes it especially easy for the prevalence of different priorities over walkability in the production and up-keep of the built environment. When legislation or its effective application falls short, urban growth follows short term financial incentives.

In the case of Turkey, urban planning and design is executed through strategic, regional, environmental, metropolitan development, master development and implementary development plans from larger to smaller scales (Yılmaz Bakır, Doğan, Koçak Güngör, & Bostancı, 2018). The plans concerned with the built environment in the neighborhood and street-scale are implementary plans prepared by local and metropolitan municipalities. Unfortunately, both the preparation and application processes fall short in regulating the built environment to benefit the social and physical well-being of the public, fueled by the conflict between the central and local municipalities (İçyüz, 2014), the amendments applied to master development plans and the gaps in urban policy.

A recently published research report co-authored by the Ministry of Environment and Urban Planning (Kenttam-MSGSÜ, 2016) points out to the absence of a holistic and comprehensive urban design policy in the country. This is the primary indicator for the lack of legislation directly concerned with walking friendly built environment design. The same document nevertheless compiles and analyzes existing legislations of all levels concerned with urban design and suggests guidelines and improvements. Within the existing legislation concerned with urban design, mentions of the necessity to carefully design pedestrian paths as well as walking and biking friendly environments, encourage non-motorized transport, improve access to public transportation and facilitate multi-modal transportation are the rare items directly related with walkability while preservation of local identity, creating sustainable environmental solutions or reducing environmental noise pollution (Kenttam-MSGSÜ, 2016) are decisions that can be indirectly linked to walkability. Based on the scarcity of the appearance of the concept of walkability in the urban design related legislation, it is not surprising that a gap exists between research and application in the design of walkable built environments. The main reason for this gap is the lack of specific codes and sanctions against practices deficient in supporting pedestrian friendly urban design. This, together with the central government's intervention in the local planning processes and the amendments applied to the development master plans allows for the prioritization of industry or project specific profits over public good as the driver for spatial planning policy and practices. Thus, shorter term financial and time-saving benefits of central and local municipal investments become the primary concern in urban design decision-making processes.

In Portugal, three levels of municipal plans shape the urban form and Plano de Pormenor (PP) (urban design plans) are the most detailed regulatory plans which concern neighborhood level planning and design decisions most relevant for walkability. They define:

> … the precise buildings' location, built-to-line, mass, height, construction area by use, materials, and colors; delineate exactly the streets' section, landscaping, sidewalks and vehicular lanes; calculate and provide for the necessary parking; define the location, general design and landscaping of parks and other open public spaces; define the dimensions and the location of public buildings; determine the necessary conservation, rehabilitation, or demolition of existent structures; and establish the phasing of the overall plan. (Balula, 2010)

According to Balula, in the case that an urban design plan doesn't exist or remains insufficient in clearly defining the formal structure of the site of intervention, the "lotaemento" (land subdivision) plans which are submitted by private developers in the licensing of each urban development project play a defining role (2010). This, and the underuse of regulamentos municipais (municipal statutes) which allows for the municipalities to specify their own urban design regulations lead to the urban design decisions and resulting interventions to be easily manipulated by market forces (Balula, 2010). Tulumello (2016) also points out to the prevalence of neoliberal policies that favor real-estate and tourism driven urban planning and design decisions primarily lead by financial incentives.

Lack of policies targeting the reduction of personal motorized vehicle use and supporting more sustainable modes of transit by improving walking, biking and public transit infrastructure, or deficits in their application to urban planning and design become more apparent in countries with lower GDPs especially in cities subject to rapid growth (Cervero, 2013). One reason behind the problem could be the lack of evidence regarding the economic benefits of walkable urban centers. Kornas et al.'s study (2017) depart from this deficit and draw out the financial benefits of investing in active transportation for municipalities in the forms of tax revenues coming from the increase in property values, consumer spending and employment in walking friendly areas. It also points out the reduced maintenance costs of active transportation infrastructure. Financial incentives should be considered along with advocating and raising awareness on longer-term benefits of designing for walkability as described by Kornas et al. (2017).

Based on these observations, we can say that tools and methods to support the design of walkable urban environments should be designed considering financial incentives and time limitations binding local authorities, minimizing required resources and provide practical solutions for implementation. Therefore, these methods and tools should utilize easily accessible data, be efficient and address an urban scale modifiable by local municipalities. Thus, the general research question to be addressed in this thesis is:

“How can walkability criteria be better integrated in neighborhood level urban design processes?”

Three major issues addressed through this research pertaining to the challenges of applying walkability principles in urban design practices are: (1) the scale of focus of a majority of walkability assessment methods being in district level and therefore leaving out urban built environment characteristics improvable by municipal design capacities which are usually in meso and micro scale; (2) the processes in acquiring neighborhood-scale urban data to evaluate walkability and inform design decisions being impractical and labor intensive; and (3) inability of walkability assessment methods to respond to the rapidly transforming nature of the urban environments.

2.2 The Problem of Scale and Detail of Analysis

The most commonly accepted and operationalized walkability indicators also known as the “D”s (Ewing & Cervero, 2010) are **density**; in the forms of residential population and residential or commercial built area densities, **diversity**; which refers to the proportions of commercial and residential land uses or existence of multiple functions within specific buffers, **destination accessibility**; which looks at the numbers of various amenities and their proximities or distances on a street network; **distance to transit**, which is calculated by the number of transit stops within a distance, number and accessibility of different public transportation facilities or the number of public transportation seats available from a given location, and lastly **design**; which incorporate various smaller scale streetscape attributes that change from study to study.

The first four of these indicators have been studied extensively and correlated with measured walking activity in various studies (Cervero & Kockelman, 1997; Ewing & Cervero, 2001; Frank et al., 2010; Ogra & Ndebele, 2013; Vale, Saraiva, & Pereira, 2016; Van Dyck et al., 2010).They essentially look at the street network configuration and the distribution of people, facilities or uses within the network in the urban context. Improving these factors require more extensive planning capacity then can be afforded by local municipalities; they concern central governments, state departments and district level urban planning decisions. Local municipalities on the other hand, are much closer to their residents and the day to day functioning of public spaces, streets and the social life facilitated by these public spaces in the city. Even though local governments have smaller budgets and can afford more fragmented interventions to the urban built environment, they have the capacity to rapidly implement and receive feedback on solutions they develop. Here, the **design** indicators become relevant, as they focus on more rapidly modifiable urban design attributes that play a significant role on walkability of urban neighborhoods (Rodríguez et al., 2008). The importance of neighborhood level built environment characteristics are also emphasized in the evaluation of walkability by Carlson et al. (2015) and Learnihan et al.'s study (2011) find that the walkability related urban attributes have the highest correlation with walking at a 15-minute-walk neighborhood scale.

As the focus is narrowed down to the neighborhood scale, the resolution of analysis expands and the 2d GIS environment and generic plan representations that are commonly worked with become insufficient in analyzing the urban built environment. This is where it becomes necessary to look at the physical environment in at least three dimensions, or even consider its temporal fluctuations throughout the daily, weekly or seasonal cycles of urban life. The study of urban physical environment at this level of detail is the subject of urban morphology, but before going deeper into the relevant 3d morphological aspects and seeking practical means to measure these, the second problem that pertains to data accessibility for neighborhood level urban built environment analysis will be dealt with in the following subsection.

2.3 The Problem of Access to Data

While the information necessary to compute the larger scale attributes of density, diversity, destination accessibility and distance to transit are now commonly accessible as census data, GIS shape files, maps and other databases through municipalities or open access maps in consensual formats and modes of representation; 3d physical attributes in the neighborhood scale are difficult to record, model, measure and also track as the urban environment constantly transforms. This is why measuring the design attributes that affect walkability starts with the problem of collecting data and requires establishing frameworks to streamline these processes. Most commonly, studies rely on field audits utilizing questionnaires, forms, photographs and video recordings that require extensive time and financial resources (Babb & Curtis, 2015) to start with. The collected information not only needs to be processed through more man-hours, it is also liable to human error and is difficult to update to reflect the ever-changing conditions of the urban environment.

What kind of data do we need to evaluate the urban environment for walkability? The neighborhood level attributes that previous studies have focused on include sidewalk width and quality (Frackelton et al., 2013; Kim et al., 2014; Özbil, Yeşiltepe, & Argın, 2015); existence, sizes, types and shading capacities of roadside trees (Harvey, Aultman-Hall, Hurley, & Troy, 2015; L. Yin, 2017); existence of street furniture (Ewing & Handy, 2009); frequency and extent of visual and physical access from buildings to streets (Beirão & Koltsova, 2015; Lopez & Van Nes, 2007); building façade shapes, colors and signages (Ewing & Handy, 2009), building heights (Lindal & Hartig, 2013), façade widths; visibility of landmarks (Bartie, Reitsma, Kingham, & Mills, 2010), landscape elements (Leslie et al., 2005), the sky (L. Yin & Wang, 2016) and various urban limits; existence and safety of street crossings (Moura, Cambra, & Gonçalves, 2017) and width to height proportions of the streets (Harvey et al., 2015). Among these vast set of indicators, some have been found to be more influential than others and means to automate the collection of some have been attempted. While measuring all is expensive, laborious, and impractical, collecting and keeping the data up to date through traditional on-site surveys is almost impossible.

This brings us to the paradigm shift in the nature of geographic data in terms of its scale, variety and speed of generation that has taken place in the recent years (Li et al., 2016). As cities grow in unprecedented speeds, computers and sensors become embedded in their daily functioning and massive amounts of data is produced with the potential to feedback and improve urban life (Batty, 2013). The term "Smart City" is used to refer to this phenomenon with a promise that computers embedded in the functioning of cities make them more efficient (Batty et al., 2012; Townsend, 2013). Big data, produced through these computers and connected sensors embedded in the built environment and hand-held devices of the urban dwellers, is subject to a large body of research aiming to make meaning out of and utilize it in designing, building and managing cities more effectively.

While these developments have influenced urban design methods through the advancement of technologies in the forms of CAD, GIS and simulation software, methods to obtain urban data and data resources available to designers, planners and policy makers have also progressed. The type of data this study is concerned with is 3d morphological data obtainable through automated methods and accessible through open source platforms or local jurisdictions. Methods to obtain data already utilized in urban design research include high resolution satellite imagery combined with image processing algorithms, 3d LIDAR data used to detect height values of buildings and roof types (Zhou, Song, Simmers, & Cheng, 2004), detect trees (Haala & Brenner, 1999) or detect road edges (Truong-Hong, Laefer, & Lindenbergh, 2019) as well as street view imagery used to train neural networks to classify streets under various perceptive qualities (Naik, Raskar, & Hidalgo, 2016). However, walkability analysis methods focusing on the neighborhood and street scale that are exclusively based on automated data collection or GIS data are still rare in literature (Purciel et al., 2009; L. Yin, 2017).

We will soon be able to capture the complete physical properties of an urban street in 3d and detail, and researchers already work on algorithms that can identify the various elements making up this physical setting and distinguish between roads, sidewalks, trees, street furniture, buildings and various façade elements. Furthermore, the automated nature of these processes implies the possibility of rapidly updating the 3d information regarding the urban morphology. What makes these technologies interesting from the perspective of this research is that, a majority of the previously listed features measured for evaluating neighborhood level walkability indicators are manifested in the 3d morphology of the city. This means that a walkability evaluation method based on processing this information obtained through satellites or LIDAR can replace the resource-intensive surveys and audits required to capture the physical aspects and condition of the built environment. Moreover, as the level of automation increases through 3d scanning, image/point-cloud processing and also in walkability evaluation processes, an almost real-time assessment tool can be constructed. A conceptual model of this tool will be presented later in this chapter.

Future projections confirm that we will have access to larger amounts of urban data at a faster pace as the technology advances, however, we need to be selective in what to measure and utilize. Filtering and making meaning out of big data are the first steps in being able to utilize it. This is one of the objectives of this thesis. It aims to reduce the multiple entities measured through morphological analysis to a representative core set and utilize them in measuring walkability. The question can be stated as follows:

"What aspects of the built environment should we look at to obtain the most relevant information for analyzing walkability and informing design decision-making processes most effectively?"

This research investigates the answer to this question via a comprehensive literature review of attributes utilized in existing walkability indices, then goes on to test a subset of these measurable based on morphology and street view image data, and finally defines a core set that the proposed workflow is most effective in measuring. Thus, the current workflow does not measure a comprehensive set of attributes, but the study is a step towards making this possible in the neighborhood scale.

2.4 Morphology as an Evidence and Indicator of Walkability

Urban morphologists have studied urban form as the tangible manifestation of social and economic forces that shape the cities since the field was born (Moudon, 1997). While the study of urban form concerns several domains including geography, archeology, history, architecture and planning, scholars from all these fields agree on the common grounds that:

1. Urban form consists of three physical components which are the building and its surrounding open spaces, the lot and the street.
2. Urban form can be studied at different levels of resolutions which are the building-lot, the block-street, the city and the region levels.
3. Urban morphology is in constant transformation and therefore needs to be studied historically (Moudon, 1997).

These principles are helpful in positioning this research within the study of urban morphology as focusing on all three physical components of urban form at the street-level and proposing a method to capture the morphological state of an urban environment at a specific point in time. However, it adopts a semi-automated and parametric analysis model to enable rapid updating and re-analysis in an attempt to respond to the urban design needs of the constantly fluctuating urban form. The resolution of the urban morphology studied in this thesis can also be better positioned between the street and the city scale, as it is concerned with the morphology in the street-level, however it explores the variations of streets' morphological characteristics within neighborhoods. Therefore, the scale studied will be referred to as street and neighborhood scale throughout the thesis.

Moudon (1997) also lays out the purposes of theory building in the field of urban morphology in three groups, adopted by different schools. Theory of city building (1) aiming to understand how cities are built, theory of city design (2), aiming to define how they should be built and design criticism (3), aiming to understand the impact of past theories on the resulting urban form. The current research seeks to establish a framework within the theory of design, specifically to provide guidance to build more walkable urban forms. However, this requires a thorough understanding of how the physical urban environment is shaped in the first place and what forces play a role in its constant transformation, in order to find potential points of intervention and develop solutions adaptable to real-life scenarios. Thus, the gaps between design theory and practice, or between what needs to be built and what is actually built, is of special concern, to identify the causes and possible opportunities for intervention.

Morphology of the built environment and walkability are known to have a direct relationship. The heights of buildings and other urban boundaries surrounding the streets; the widths of streets and sizes of public plazas; variation of façade shapes; massing configurations that affect outdoor climatic conditions, entrances and openings of building facades; the existence and shading capacities of street trees; the connectivity and other syntaxial properties of the street network are all such morphological aspects proven to affect how walkable an urban environment performs. On the other hand, walkability of an urban environment is not solely dependent on the physical built environment. Local policy; economic and social conditions as well as cultural aspects play a role in how physically active their inhabitants will be (Forsyth, 2015). Also, several elements that are part of the built environment are not directly related with morphology. Residential density, land use diversity, availability of public transport and amenities cannot be attributed to morphological factors. However, a street and neighborhood level analysis of urban morphology can reveal evidence for some of these factors (Oliveira, 2013; Oliveira & Medeiros, 2016). It can act as a snapshot of the existing conditions from which several of such factors can be inferred (Moudon, 1997).

Thus, we can say that the built environment of certain morphological characteristics may be an evidence of and will be more likely to facilitate conditions that support walkability. Higher levels of residential density, land use diversity as well as accessibility and variation of amenities are among such aspects that this thesis proposes to infer from measured morphological attributes and link with walkability related built environment characteristics.

Finally, discourse on urban data inevitably draws attention to the velocity of its production pointing out the constantly evolving, growing and transforming nature of cities. Thus, besides making use of constantly generated data in the urban environment, this thesis is also concerned with capturing and being able to respond to the constantly transforming nature of these environments. Hence the next question this research deals with can be stated as follows:

"How can we analyze the walkability conditions of the highly complex and constantly transforming urban built environment in the neighborhood level?"

2.5 How to Assess a Physical Environment in Constant Flux

Cities are often compared to living organisms in terms of their complexity and constantly transforming nature due to the continuous interchange between the systems within and outside of themselves. Beirão (2012) uses the term "flexibility" to refer to the urban design approach required to address this constant flux. He explains that firstly, the design methods need to be flexible so that they respond to the constantly transforming design problems; secondly, the designs should be flexible so that they are not singular but they offer systems of solutions adaptable to design problems; and thirdly, the final design solutions should be flexible so that they allow for changes and adaptations after implementation (Beirão, 2012).

Several design thinking methods and tools are relevant for flexibility within the broad context of urban design. In approaching the problem, to be able to evaluate built environment attributes in the neighborhood level, this study utilizes a workflow combining visual programming with a 3d parametric model and GIS as well as web-based, geo-located urban data. It facilitates the first type of flexibility Beirão mentions through an algorithmic model that has the potential for integration with rapidly updateable data sources and generative processes. The algorithmic model allows for a semi-automated workflow intended to be developed into a fully-automated model to facilitate integration with automatically updated data sources providing input, and generative design methods utilizing its output. Even though generative design approaches are outside the framework of the research, design recommendations will be developed that define solution steps applicable in multiple scenarios, therefore the second type of flexibility through systems of solutions (Beirão, 2012) is also a goal.

Ultimately, the walkability evaluation workflow proposed by this research is intended as a preliminary model for a tool that can become a part of a flexible urban evaluation and design support tool, also involving generative methods. The conceptual model of this tool is presented below (Figure 2.1). At the core of this conceptual model is a frequently updated 3d urban model, which is evaluated by the proposed workflow (and eventually the tool) that generates design recommendations (and eventually design-solution sets) for improvement. Implementation of the solutions is registered into the

3d model that is updated together with any further changes in the urban built environment, and the model is re-evaluated to suggest further improvements. The more frequently the changes in the built environment are registered to update the 3d model, the faster it can run evaluations and respond with improvement solutions. Considering the fast-paced developments in the sensor technologies, LIDAR and satellite imaging systems discussed in the subsection 2.3, the possibility of generating and maintaining urban models that reflect the changes in the urban environment in real-time does not seem far off.

The walkability evaluation workflow that this research proposes is seen to have a potential to become one part of the many urban assessments performed through analyses and simulations such as climatic conditions, energy consumption, traffic flows, noise and alike (Figure 2.1). The generative solutions fed by these evaluations can be integrated into design processes and also be optimized. In such a scenario, the implementation of the generated design interventions would go through additional evaluation of benefits and costs performed by the administrative bodies and alterations would be fed back into the 3d urban models.

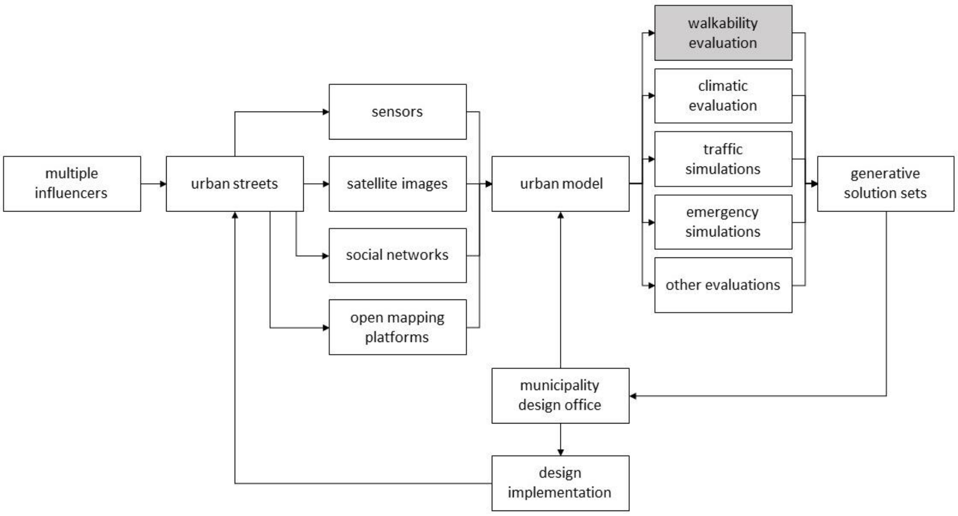


Figure 2.1 : The conceptual design support model this workflow is to be a part of.

With such a conceptual urban design support model in mind, the current workflow (Figure 2.2) utilizes fully algorithmic and semi-automated processes, intended to be further automated by the integration of cloud-based databases fed with real-time data and converted into a set of tools through future study.

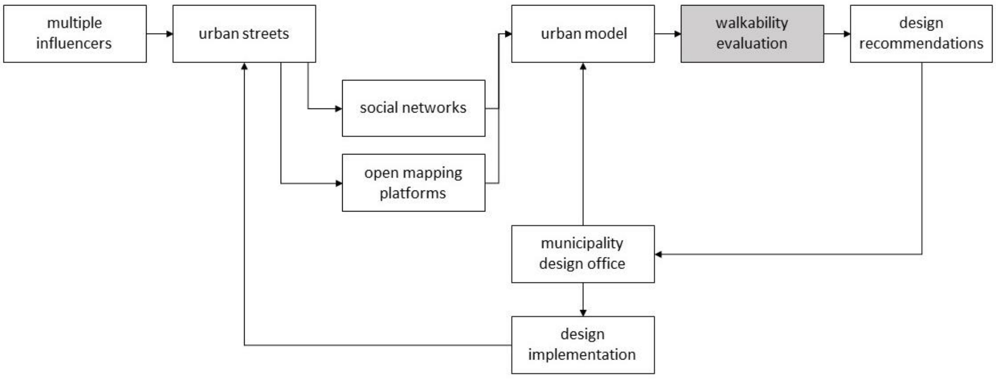


Figure 2.2 : The current workflow within an urban improvement scenario.

2.6 Expected Outcomes

Aiming to answer the questions posed in this chapter, the thesis proposes that (1) neighborhood level urban design decisions can be improved in terms of walkability through a semi-automated workflow relying on openly accessible geographical data and a parametric 3d model; (2) a core set of morphological attributes can account for a majority of walkability related urban built environment characteristics and (3) new data sources, collection and processing methods can highly benefit urban evaluation processes, especially walkability focused analyses.

At successful completion of this research, it is anticipated that the recommendations to be produced as an output will act as a guide for urban interventions with shorter timeframes. The developed walkability assessment workflow is intended to be useful as consulting services to municipalities and private investors in guiding their urban design project processes for larger scale interventions. In further stages of development of the workflow following the completion of this thesis, as the automation is improved with reduced software and plugin dependencies and better integration with database management systems, parts of or the whole assessment method can be utilized by third party designers and decision-making authorities as well as being integrated into larger urban assessment processes. Steps to facilitate this have already been taken by the launching of a website (Ensari, de Klerk, & Beirão, 2018) for the utilized Convex and Solid-Void analysis that include the software tools and their guides as well as the publication of a paper on the web scraping methods employed to collect location based urban data (Ensari & Kobaş, 2018).

3. STATE OF THE ART

3.1 Walking in The City

Before the invention of the automobile, traditional towns naturally evolved around or were planned for the pedestrian. The industrial revolution in the second half of the 19th century brought factories into the cities and living conditions in the centers deteriorated because of pollution, and rapid densification due to the influx of workers and their families without sufficient infrastructure to accommodate them. Modernist urban planning of the 1930s introduced the idea of separating the residential and the industrial zones in an attempt to provide better living conditions for the people. The vision for the new residential architecture entailed providing more green space, air, and sunlight to its residents for which buildings would be oriented towards the sun rather than the street (CIAM, 1933; Gehl, 1987). Supported by the advent of the automobile, this vision was put into action through expanding cities by building separate residential, commercial and industrial zones as well as kilometers of highways to connect them. As the number of car owners increased, suburbs grew, cities emptied and traffic congestion became one of the biggest problems of cities followed by pollution. Health problems related with immobility started affecting large percentages of populations. The residential typologies of the housing block, the suburban villa and the gated community created their own set of social, health and safety problems by redefining neighborhood relationships and spatial ownership.

Following the failure of the modernist urban planning practices that focused on efficient transportation of humans and goods between carefully separated living and working quarters of cities, urbanists started drawing attention to the naturally prosperous social and economic life in the dense urban centers as opposed to the deteriorating public life in the suburbs (J. Jacobs, 1961; Whyte, 1988). They emphasized the need to focus on comfort and use conditions of urban public spaces for people, criticizing the modern cities being planned around motor vehicles (C. Alexander & Silverstein, 1977; Gehl, 1987; J. Jacobs, 1961). The urban built environment was studied from the point of view of the pedestrian, identifying the components required for a vibrant public life lost in the newly emerging modern cities (Cullen, 1961; A. Jacobs & Appleyard, 1987; Lynch, 1960). Urban squares and streets as public spaces were re-considered as facilitators of a vivid social and economic urban life and thus valuable assets of a healthy city (Childs, 2004; J. Jacobs, 1961), and the behaviors of their occupants were meticulously studied to understand how these spaces could be better improved through urban policy, practice and design (Gehl, 1987; Whyte, 1980).

The emphasis on the need to design cities prioritizing the pedestrian consistently appears in this literature and the principles spelled out are now commonly utilized in walkability research. Yet "walkability" as a term did not appear in literature until the early 90s owing to an attempt demanding to exempt walking-friendly neighborhood residents from tax raises related to road maintenance costs (Cambra, 2012). Walking as a healthy and socially engaging means of transportation and built environment factors affecting it were primarily studied within urban planning and transportation research until the late 90s. Later, health researchers became interested in walking as a means of physical activity and started contributing in this research (Sallis, 2009). Through the following studies conducted by researchers in the fields of health, urbanism and transportation, there came to develop a consensus on the associations between the benefits of walking with the wellbeing of the populations and their walking behavior with the built environments' physical qualities.

Both the research on more liveable and people friendly public spaces as well as that which focuses specifically on walkability led to the development of auditing methods and guides for urban planning and design (Childs, 2004; Ewing & Handy, 2009; Gehl & Savare, 2013; Institute for Transportation and Development Policy, 2018; Methorst et al., 2010; Project for Public Spaces Inc., 2015). The principles behind these audits and guides are based on the aims to preserve and enhance the local identity of neighborhoods; provide safe, comfortable, accessible and attractive public spaces for the citizens of different ages and physical capacities; improve green and local transportation infrastructure and encourage sustainable mobility through regulating the designs of sidewalks, storefronts, street furniture, lighting, parking and vegetation in streets, squares and other public spaces. Learning from this large body of research, several cities adopted these planning and design principles in their urban design guides and codes, and today, have well established design guides and standards (Bain &

Sizov, 2013; City of Melbourne, 2013; City of New York, 2013; City of Voncouver, 2018; Cornog & Gelinne, 2010; DCOP, 2011; Mead & Mentz, 2002). However, walkability and place making principles aren't prioritized or manifested equally in cities all over the world. In developing countries and the middle east, the awareness on the issue didn't develop until recently (Cervero, 2013; Zohadi, 2012) and implementation of these design strategies have been local and limited (Abu Dhabi Urban Street Design Manual, n.d.; Skaufel et al., 2013).

Forsyth (2015) groups the references to the term "walkability" under three types of usages in literature. The first usage pertains to the physical conditions such as transversability, compactness, safety and attractiveness (Forsyth, 2015). The second is related to the perceived outcomes of the conditions that make a place walkable such as liveliness and sociability, public transport friendliness and capacity to induce exercise (Forsyth, 2015). The third use refers to either the holistic meaning indicating healthier, happier and more human friendly urban environments or indicates the multidimensionality of walkability as a quantitatively measurable construct (Forsyth, 2015). The physical conditions referred to in the first use are constituents measured by the multidimensional constructs or walkability indices that the third use refers to. This thesis utilizes the term as it is referred to in the third group of uses as a multidimensional construct and the next section goes into detail about the multiple dimensions of this construct as well as various measuring methods developed to evaluate it.

3.2 Measuring Walkability

This section looks at the various disciplines and their approaches in measuring walkability, the walkability audits, indices and other evaluating instruments available today; ranges of scale these measures were developed for as well as the several urban qualities that have been considered as indicators contributing in them.

The vast body of research on the urban livability and walkability is the product of a few fields. A majority of such studies are conducted by public health researchers, and draw out positive correlations between walkability of urban environments and physical activity of their inhabitants which is known to affect the rate of obesity and related diseases (Brown et al., 2009; Ewing, Handy, Brownson, Clemente, & Winston, 2006; Frank, Schmid, Sallis, Chapman, & Saelens, 2005; Kornas et al., 2017; Purciel et al., 2009; Saelens, Sallis, Black, & Chen, 2003). Their purpose is to urge the improvement of physical conditions of the built environment and of administrative strategies to enhance pedestrian mobility, encouraging physical activity especially as a means of transportation. Transportation engineering, more closely related with urban planning, is another field of research that focuses on walkability. In these studies, walking is considered as a sustainable mode of mobility along with the use of bicycle and public transit (Cervero, 2013; Cervero, Sarmiento, Jacoby, Gomez, & Neiman, 2009). Their goal is to encourage public spending on the improvement of the pedestrian infrastructure and other features of the built environment contributing in the increased use of sustainable transportation. These studies aim not only to increase citizens' walking to destinations but also to ease their access to public transit, as walkable environments encourage more frequent preference of public transportation over personal vehicle use and reciprocally, the use of public transportation encourages more walking. Walking as a means of transit has been distinguished from recreational walking and utilized more often in walkability studies (Forsyth, 2015) as it was found to be more closely associated with the built environment qualities than did recreational walking (Saelens & Handy, 2008) and the difference in the distances walked between walkable and non-walkable neighborhoods were due to residents walking for utilitarian purposes (Rodríguez, Khattak, & Evenson, 2006) rather than recreational.

While research in the health and transportation can influence the policy makers, planners and administrators in building and managing cities to provide more walkable conditions, studies carried out in the fields of planning and design have the power to directly affect the walkability of the newly built and restored environments through informing and improving design methods and processes. Through the introduction of algorithmic methods and automation into architecture and urban design, it has become easier to evaluate walkability of existing streets and design proposals, and furthermore it is now possible to use walkability as a criterion in generative design processes (Blečić, Cecchini, Fancello, Fancello, & Trunfio, 2015; Blečić, Cecchini, & Trunfio, 2017; Rakha & Reinhart, 2012; Reinhart, Dogan, Jakubiec, Rakha, & Sang, 2013). Even though such approaches are not commonly utilized in everyday urban design practices, the methods and tools for measuring walkability bare utmost importance to facilitate the integration of walkability measures with the rapidly evolving design and planning professions. The implications of the technological advancement of design methods for walkability will be explored later in this chapter.

The detail and scale of evaluation of the built environment for walkability is closely related with the impact on the built environment that can be afforded through urban design informed by the evaluation. How much the walkability measurements can inform urban environments also depends on the scope of interventions that the city authorities at different levels are responsible for. Thus, studies on walkability should consider at what level of urban administration and scale of urban design the research is intended to be operationalized. The scales defined for the developed indicators range from macro to micro. Macro scale evaluations measure residential or commercial density, connectivity of road networks and diversity of land-use, configuration of street networks, demographics and accessibility (Frank et al., 2010, 2005; Giles-Corti et al., 2014; Leslie et al., 2007), while micro-scale measures are concerned with a much higher level of detail assessing street-level features like sidewalk quality; noise; the existence of greenery, landscape or historical features, street furniture, people and activities (D'Alessandro, Appolloni, & Cappuccitti, 2015; Ewing & Handy, 2009). In many cases, as for the measures referred to as 3Ds, 5Ds, 6Ds or 7Ds that are to be explored later, the majority of the indicators work in macro-scale while one of the D dimensions pertain to Design, which is concerned with either street network characteristics that are sometimes referred to as Connectivity and/or smaller-scale built environment attributes. Meso-scale features are less consensual; Harvey proposes a measure named "Skeletal Streetscape" as meso scale that measures cross sectional proportions and length and width of streets, density of buildings, as well as shading capacities of the trees on the street (Harvey, 2014) and Cambra (2012) suggests that accessibility of destinations through the street network should be considered a meso-scale indicator. As also previously mentioned, to overcome the lack of clarity in the terms used to refer to the scale of measured built environment characteristics, this thesis refers to the morphological and streetscape characteristics studied as "street and neighborhood" scale.

Several of the walkability measures found in literature are in the form of composite indices, where a number of urban attributes namely "indicators" are quantified, assigned weights based on how much influence they have on the measured outcome and combined together into a single score or a small number of scores (Brewster, Hurtado, Olson, & Yen, 2009; D'Alessandro, Assenso, Appolloni, & Cappucciti, 2015; Ewing & Handy, 2009). The indicators are sets of attributes contributing to various scales of evaluation as explained above, and their extent of influence on user perception, preference or walking behavior is calculated through statistical correlation in order to derive weights to be utilized in these composite scores.

Initially defined as the "3Ds" (Cervero & Kockelman, 1997) Density, Diversity and Design are the most widely accepted indicators of the built environment that have been linked with pedestrian activity (Ameli, Hamidi, Garfinkel-Castro, & Ewing, 2015; Ewing & Cervero, 2001, 2010). The 3Ds have been expanded to 5Ds to include destination accessibility and distance to transit with studies that followed (Ewing & Cervero, 2001) and later to 6Ds (Ogra & Ndebele, 2013) and 7Ds with the addition of demand management and demographics (Ewing & Cervero, 2010). "5Cs" are another set of indicators, specifically developed to assess the street network and comprise Connectivity, Conviviality, Conspicuousness, Comfort and Convenience (Gardner, Johnson, Buchan, & Pharoah, 1996; Pharoah, 2005). Among smaller scale measures, Imageability, Enclosure, Human scale, Transparency and Complexity are used to explain the above mentioned indicator of Design as part of the "Ds" and are some of the most commonly referenced indicators in walkability literature (Ewing & Handy, 2009; Purciel et al., 2009; L. Yin, 2017). Brief descriptions of these indicators are presented below (Cambra, 2012; Ewing & Clemente, 2013).

Density, measured by the indicators of housing density; building density; gross floor area ratio and housing gross floor area ratio, is defined as "the variable of interest per unit area" by Ewing and Cervero (2010) where interest may represent population, dwelling units, employment or other activity.

Diversity, also referred to as entropy, mixed-use or land-use measures, evaluate the ratios of square meters of different land uses found in areas that are assessed. Among the many computations to measure diversity, percentage of single-family buildings, percentage of residence dwellings, percentage of different types of commercial uses or services and percentage of area occupied by activities are a few examples.

Accessibility, measures availability of various amenities and attractions within specific walking distances. It can be measured using distance to the closest activity, average distance to closest n number of activities; number of activities within specific network distance or within a specific walking time. The utilized network distances vary among authors but 400m, 800m and 1200m or distances walked within 5, 10 and 15 minutes are commonly used. The measure sometimes referred specifically as “distance to transit”, or “transit accessibility” may be calculated by distance to the closest transit stop; transit supply in the closest transit stop, types of available transit options within a certain walking distance of time, total distance accessible by transit within specific time periods and transit frequency.

Design indicator varies greatly from study to study; in some, it refers to smaller scale attributes such as the sidewalk quality, proportion of street cross sections, existence of landscape elements and vegetation or building façade features. In other studies, it pertains to the street network design that is otherwise referred to as connectivity.

Connectivity refers to the number of intersections on a street network and is measured by the indicators of node density; pedestrian shed ratio; straightness and average link length. Sometimes, connectivity is dealt with as part of the Design indicator under the “Ds.”

Conviviality refers to the extent to which an environment is attractive, lively, entertaining and sociable. Some of the various elements have been taken into account measuring this indicator are street furniture, frequency of people seen on streets and qualities of building facades and street walls. It is similar to the complexity indicator.

Conspicuousness is about how legible, easy to navigate, clear and distinct an environment is to the pedestrian. It takes into account street signs, building setbacks and enclosure.

Comfort refers to how comfortable an urban environment is to the pedestrian. Protection from the weather elements, the design of the sidewalks and how accommodating they are, how safe it feels to the pedestrian are related to the comfort indicator.

Convenience refers to how practical, suitable and appropriate an urban environment is for pedestrian access. Multiple attributes of the streets are taken into account which also fall under Landuse and Sidewalk sub indicators in literature (Cambra, 2012).

Imageability, Enclosure, Transparency, Human Scale and Complexity are sometimes considered as part of the Design indicator or they are used specifically as part of neighborhood scale indicators.

Imageability indicates how memorable a street space is and it is measured by the number of historic elements, landscape features, existence of street furniture and outdoor dining facilities. Theoretically, it is based on the seminal book “Image of the City” by Lynch (1960) that promotes focusing once again on human experience when designing urban environments.

Enclosure is measured using sky view factor, height of buildings and street wall continuity. Better enclosure is considered to enhance walkability based on the assumption that people feel safer and more comfortable in room-like spaces and better enclosed outdoor spaces reinforce this feeling.

Transparency is measured by the proportion of window openings to walls on building facades. It is believed that the more variety of active facades a pedestrian sees while walking, the less they will be bored and the shorter their walk will feel.

Human Scale is measured by building heights, the number of street furniture, proportion of windows on facades, existence of uninterrupted sight lines as well as the speed of traffic**.** Walking along an empty highway is considered unpleasant due to the high speed of traffic being out of human scale and there being no relatable street elements that keep a street interesting and active.

Complexity is measured using number of people, buildings, primary and accent façade colors, existence of furniture and public art. It is concerned with elements that keep a street lively, interesting and attractive with enough stimuli to keep a walker engaged.

Technologies that have become available to researchers are also definitive for the methods developed to evaluate walkability of the urban built environment. GIS software are highly practical in evaluating urban environments, due to the ease of obtaining and operating with large amounts of geographically linked geometric and semantic data. Generally, the measuring methods at macro scale that are based on indicators such as density, connectivity and land use mix can easily be digitized and calculated through GIS (Agampatian, 2014; Aultman-Hall, Roorda, & Baetz, 1997; Frank et al., 2005; Giles-Corti et al., 2014; Harvey et al., 2015). As the level of detail to be measured regarding an urban environment increases, it gets more difficult to obtain relevant data in GIS format, thus making it harder to automate the process and assess larger urban areas at once. Such measuring methods usually rely on in-person audits (D’Alessandro, Appolloni, et al., 2015; Ewing et al., 2006; Pikora et al., 2002), which are effective in collecting information about the physical qualities of the built environment that directly influence the perception of the pedestrians. These measures can assess particular features in detail such as how well a sidewalk is maintained, how safe a street crossing is, the noise level of the street, or the presence of artwork, street furniture, lighting fixtures or landscape elements on a street. On the other hand, in-person audits tend to be expensive, inefficient and unreliable (Babb & Curtis, 2015; Harvey, 2014).

In Purciel and colleagues' study (2009), urban measures calculated through the detailed and small-scaled features of urban design were partially adapted to GIS, and sample areas in New York City were audited for the same measures, concluding that a majority of measures could be accurately calculated through GIS. In another study, through the use of 3d GIS and Google Street View imagery, these measures were extended to include more indicators that were initially not possible to compute through GIS (L. Yin, 2017). The significance of this study as a precedent for this thesis is twofold. Firstly, the scale of analysis that considers streetscape attributes is deemed important due to being modifiable through local municipal urban design interventions and the influence of measured attributes being in the neighborhood scale. Secondly, the use of GIS and additional automated methods allow the analysis in this scale to be efficient and objective as opposed to previously used surveys and audits requiring extensive resources in terms of time, money and man-hours as well as being prone to human error. Both these issues are part of the problem pertaining to the measuring methods of walkability that this thesis aims to address and they will be explained further in the following sections.

3.3 Morphology in the Neighborhood Scale as an Indicator of Walkability

As explained in the previous section, studies utilize several indicators to measure walkability. This thesis is specifically concerned with the morphological aspects or the aspects that are expressed and therefore are possible to measure through the morphology of the physical environment. Thus, it will be useful to look into what the term "morphology" refers to in walkability literature, studies specifically concerned with morphology of the built environment and methods developed to analyze the morphological properties of the built environment whether they are directly concerned with walkability or not.

Urban morphology is an area of research which studies urban form and concerns researchers from fields of architecture, geography, planning and history (Moudon, 1997). Urban morphologists analyze the city through its physical components, considering its formal elements as the tangible results of the social and economic forces that shape the city. As defined in the previous chapter, urban morphologists agree on three principles of research in the field. Firstly, that urban form is defined by three elements: buildings with their surrounding open spaces, plots, and streets; secondly, that urban form can be analyzed in different levels of resolution: building-lot/street-block/city/region and thirdly, that urban form can only be understood historically as its constituents are in constant transformation (Moudon, 1997).

Morphology has been strongly associated with various phenomena and investigated as a means to explain economic, social and political forces shaping the urban environment. Stojanovski (2018) argues that physical form emerges as a result of certain economic and development patterns, and then is appropriated by social groups, forming neighborhood types which become indicators of social class. Oliveira and Medeiros (2016) have developed an analysis method that evaluates the relationships between streets, plots and buildings through seven measures to determine different levels of urbanity, being able to infer whether a neighborhood is urban or suburban based on these physical relationships. Pont and Haupt (2005; 2010) define four density variables merely based on urban morphology, and using these variables they are able to describe several land development typologies.

Walkability research has utilized urban morphological measures at resolutions of building-lot, street-block and city level. Space Syntax (Hillier & Hanson, 1984) is one of the pioneering and most utilized computational methodologies of urban morphological analysis and it provides a number of measures to topologically evaluate the street network configuration. The method originates from the theory that street network configurations determine the pedestrian movement patterns in the city and thus, influence spatial distribution of various demographic, economic and social phenomena. Street network measures constitute the core indicators for several walkability indices, usually as part of Connectivity and Accessibility measures (Brewster et al., 2009; Ellis et al., 2016; Özbil et al., 2015; Pikora et al., 2002; Saelens, Sallis, & Frank, 2003), even though accessibility measures also require metric information not utilized in Space Syntax methodology. They are relevant for walkability analysis in all scales, but are most commonly utilized to calculate distances to amenities and intersection densities in macro and meso-scale analysis. As an automated method primarily requiring the street network geometry for analysis, Space Syntax can be practically applied in regional and city scales, however, this methodology has been criticized for excluding a wide-range of morphological information regarding the built environment, especially concerning the 3d features such as topography, building heights and more detailed physical attributes of streets such as the street widths and width ratios of pedestrian to vehicle lanes (Ratti, 2004). This thesis utilizes Convex and Solid-Void models, which constitute a method that was developed to address these shortcomings in the morphological analysis of the urban built environment, originating from the convex space concept present in the Space Syntax methodology (Beirão et al., 2015, 2014; Čavić et al., 2017; Sileryte et al., 2017). The method allows for the analysis of urban open spaces through a GIS and a 3d model and identifies several morphological attributes that in this research are utilized to assess walkability.

Analysis of urban morphology usually remains in 2d in larger scales of evaluation and traditional GIS methods also utilize a 2d graphical interface. Even though 3d analysis has been possible through utilizing attribute values for 2d geometric entities and 3d interfaces in GIS environments are now becoming available, GIS environments have remained more suitable for 2d analysis until recently. However, as the scale gets smaller and detail of physical features to analyze increases, 2d information regarding morphology becomes insufficient. Common walkability indicators of density, land-use mix or diversity, accessibility of transit and destinations or connectivity are calculated through GIS maps with roads, zoning and census data. The measure of design that require more detailed information such as sidewalk quality, landscape elements and vegetation, buildings' facade qualities, street furniture, lighting and noise cannot be computed through readily available data in formats suitable for 2d maps and traditional GIS applications. The data needed to measure these indicators are usually acquired through field audits and surveys that are time and moneywise inefficient, with the results being prone to human error and bias. It is also burdensome to maintain and keep this kind of data up to date. Nevertheless, some studies have found local scale built environment characteristics in the neighborhood and street-level to be highly influential in the walking behavior of urban inhabitants (Carlson et al., 2015;

Learnihan et al., 2011). Moreover, facilitating urban design improvements for more walkable neighborhoods is greatly dependent on being able to inform local decision makers regarding modifiable physical environment features influencing walkability in this scale (Rodríguez et al., 2008). Two trends in urban analysis and design practice are helping overcome the limitations in analyzing neighborhood and street-level physical environment characteristics. First is the advance in the computational methods and subsequent improvements in automation, and the second is the big data boom following the spread and integration of sensors, software and platforms in our cities. The next sections will provide overviews of these two factors in the transformation of the urban analysis and design, focusing on their implications for walkability research. These developments are of particular interest for this research as they are seen as essential for practically assessing the morphology of streets in the neighborhood scale which is proposed as an evidence of and will be utilized to measure several aspects of walkability.

3.4 Parametric Methods in Urban Design, 3d GIS and CIM

Today, CAD tools which enable the representation of design elements in 2 and 3d have almost become an extension of the architect and urban designer at every step of the design process. Through the introduction of parametric models and building information modeling tools (BIM) in which geometrical entities are inherently linked with semantic information, architectural design processes were infinitely enhanced to better capture site conditions; coordinate the consequent design of multiple systems; document, visualize and speed up design and construction. A similarly game changing development for urban design and planning practices came in the form of geographical information systems (GIS) (Moudon, 1997) where 2d representations of objects were linked with not only semantic information but also geographical location. Simulation and analysis tools in multiple design scales facilitated the testing and evaluation of the modeled designs' material behavior, climatic response, energy consumption as well as various use and occupation scenarios against user-provided criteria. As programming languages became more user friendly and open source, and as their editors were integrated into these design tools' interfaces, they started to be utilized by designers as well, and brought in additional algorithmic methods to the design practice. Generative programs such as genetic algorithms, L-systems and agent-based simulations became ubiquitous as support tools for generation, simulation and optimization in various scales of design.

The leading developments in the urban design practice that are pushing it to the next level are the design methods and tools that provide web-based “cloud” platforms allowing for the remote storage, processing, visualization and coordination of data, that make it possible to incorporate big data in design decision-making processes in real-time and collaboratively as well as those that integrate several of these capabilities within single platforms (Santana, Chaves, Gerosa, Kon, & Milojicic, 2017). These design-support methods and tools improve the design process through integration with large datasets, enabling the design solutions to be backed with the most recent and objective information. They facilitate the automated solution of several tasks therefore speeding up multiple processes and even provide real-time analytical feedback. Ultimately, the most advanced platforms are intended to seamlessly integrate multiple stages and component systems of design to provide the designer and decision makers the most efficient, evidence-based and flexible design solutions with the highest impact overtime.

One example of design tools that integrate the formulation, evaluation and generation of design solutions in the urban scale is the City Induction Research Group’s city information model (CIM) incorporating a GIS platform, databases, and a visual programming environment Grasshopper within a 3d CAD software Rhino3d (Duarte, Beirão, Montenegro, & Gil, 2012). Another is the Decoding Spaces Toolbox plugin that facilitates the use of various design generation and evaluation techniques in the same visual programming environment (Bielik, Schneider, & Koenig, 2012). Both these toolkits originate from a rule-based, parametric design understanding and were designed to work in a 3d modeling environment commonly used by architects. A different example is ArcGIS, which was developed through the expansion of ESRI’s GIS platform initially aimed for mapping geographical information, through products now enabling the creation of 3d models, analysis, visualization, integration with urban databases and web interaction. Since ESRI’s products are based on a GIS platform, the scale of urban planning and design operations enabled by the software is larger and the processing is faster than the previous two examples. However, the 3d capabilities are limited and precision is incompatible to work in smaller scales compared to that of 3d CAD environment integrated systems like the City Induction and Decoding Spaces tools. Due to these limitations, the algorithmic approaches including generative methods originating from design theories such as shape grammars are developed and integrated with CAD based software much faster than the GIS, nevertheless, GIS integration remains crucial for larger scale analysis and design.

Walkability research has produced several guidelines, methods and tools for the analysis of the urban built environment based on quantitatively measurable criteria, and a majority of these have been developed for or were adopted to the GIS environment (Aultman-Hall et al., 1997; Purciel et al., 2009), allowing for the rapid analysis of urban environments for their level of walkability. However, due to the limitations in 3d, smaller scale and higher precision representation and analysis, these methods and tools have remained restricted to a few examples (L. Yin, 2017). Additionally, the collection of small-scale built environment data such as sidewalk quality, vegetation or building façade qualities required the use of on-site audits which hampered automation, slowing down the process and raising the dependency on larger resources. Here, the integration of walkability analysis methods and tools not only with design software but also with data sources become critical. This is why GIS remains a crucial component for walkability analysis as it allows for computation with urban scale databases as well as geographical data. Even though limited in terms of the indicators and scale of physical features assessed, a few evaluation plugins available for design software also perform walkability analysis (Reinhart et al., 2013).

The current research addresses the gap apparent in the context of computational design tools specifically aimed at analyzing the built environment for walkability. Besides overcoming the limitations mentioned above, through future research it is also intended to become a part of a design framework that seamlessly integrates several design stages as described in the previous paragraphs.

The following section delves into the implications of big data in the contemporary urban design practice as well as the potentials it offers for walkability research.

3.5 Big Data and Its Implications for Walkability Evaluation

Urban populations have grown to the extent that more than half of the world's population lives in urban areas today. Simultaneously, through the advance of technology, computers have become embedded in the functioning of several systems making up the cities. Through these computers, the introduction of sensors to receive information and feed back into these computerized systems as well as the use of smart cards and smartphones by urban dwellers, a large amount of data has started to be generated and stored as a record of spatial and temporal phenomena in the cities (Batty, 2013). This data is called “big data” due to its scale and is attributed the characteristics of (high) volume, velocity and variety. This section will explore the potentials of big data for urban design, its sources relevant for urban analysis, methods to integrate it in design software and more specifically will discuss these issues from the focus of walkability analysis.

Urban data linked with geolocation information or namely “geospatial data” have become subject of interest to a substantial body of research. Mobility patterns of urban dwellers, traffic patterns, demographic data collected by governments and NGOs, real estate prices, voluntarily contributed data from location sharing services and social media posts are examples of data that are being collected, analyzed and visualized (Ensari & Kobaş, 2018; J.-G. Lee & Kang, 2015) in order to support urban management and planning decisions as well as to raise public awareness regarding distribution of resources and services within cities. Urban analysis utilizing LBSM and LSS data and open source street view imagery have begun to replace traditional surveys and audits as these sources prove to be more convenient, easier to access, spatially extensive and up-to date. Cranshaw et al. (2012) use Foursquare check-ins and the demographics of users for a city-scale analysis, identify clusters they call Livelihoods and through them, detect dispersion patterns in the city. Their findings are validated through interviews with the locals. One study reports the effective use of Panoramio, Instagram, Google Search Data and Foursquare to characterize a developing urban area in Amsterdam through distinguishing its “important” places based on geo-tagged, online network data maps that were used in participatory design sessions with the stake holders to plan further research (Niederer, Colombo, Mauri, & Azzi, 2015). LBSM data proves even more effective compared to traditional data sources when exploring urban mobility patterns of residents, as it does not tie people to their registered home address but enables the mapping of their locations wherever they check-in and geo-tag their posts (J. Yin, Soliman, Yin, & Wang, 2017; Zook, Shelton, & Poorthuis, 2017).

Challenges and limitations of working with LSS or LBSM data such as Facebook places, Instagram, Foursquare and Twitter are mentioned in studies as well. Firstly, this data is generated by a limited sample of the population who owns cell phones and utilizes social media apps often, immediately excluding small children and the elderly. Secondly, GPS signals are not consistently accurate in detecting precise location, and users do not always tag their locations correctly. Promotional content posted by place owners may be misleading if not filtered in post counts. Also, recent changes in US and European law regarding intellectual property rights of social media data is limiting its potential use in research (Brooks, 2018; Sanford, 2018). GPS data from smart phones and other tracking devices is also utilized to capture mobility behavior in walkability research and yield much more precise location information, however are hard to obtain and are restricted in terms of sampled users and geographic extent. LBSM data on the other hand can be attained almost globally, freely and can capture temporal changes in urban behavior.

Another revolutionary advancement in the data analytical research results from the combined use of urban image data captured and made available in various scales and machine learning technologies used to analyze them. Image processing algorithms used to analyze satellite imagery can be trained to identify real estate prices (Bency, Rallapalli, Ganti, Srivatsa, & Manjunath, 2017), detect landcover, vegetation, vehicles, specific building material as well as physical changes in the urban landscape (Zhu et al., 2017).

Street view imagery from online open sources such as Google Street View or Bing Streetside is especially valuable for walkability research and is already being used to identify built environment attributes (Ewing & Clemente, 2013; S. Lee & Talen, 2014; L. Yin, 2017) and pedestrian counts (Campanella, 2017). Their automated analysis through trained machine learning algorithms however, introduce a different level of efficiency by dramatically reducing the required hours of manual work. Even though it was done manually, Google Street View images were found to be highly effective in identifying urban built environment features (Ewing & Clemente, 2013; S. Lee & Talen, 2014) and in combination with image recognition algorithms, they have been utilized to count pedestrians (L. Yin et al., 2015), detect enclosure (L. Yin & Wang, 2016), identify vegetation, buildings and sky (Naik et al., 2016), urban change (Naik, Philipoom, Raskar, & Hidalgo, 2014) and even how they will be perceived by city dwellers (Naik et al., 2014). These studies demonstrate a major leap in the methods and supporting technologies utilized for quantitatively measuring the physical attributes of the built environment, and point to great prospects for walkability research. The research presented in this thesis utilizes some of these methods as part of an automated walkability assessment workflow, relying on the potential in their development to enable seamless collection and processing of data of the urban physical environment which can be integrated into comprehensive design frameworks in future research.

4. METHODOLOGY

4.1 Overview and Terminology

This section provides a review of urban built environment qualities that are important for walkability, and explains the choice and categorization of the attributes that constitute the measuring method and workflow developed in this thesis. Then, the proposed methods establishing the workflow will be laid out. Firstly, the terminology used to refer to the aspects of the built environment that are measured will be clarified. Next, a list of aspects to be measured in this study and their proposed categorizations supported by literature will be explained. Finally, three semi-automated techniques to gather and evaluate the data that constitute these measures will be introduced. Their application will be demonstrated through four case studies in the next chapter.

The terminology used to refer to the qualities measured to evaluate walkability from more general concepts to specific properties varies greatly in literature. In this thesis, “characteristics” will be the term used to refer to the most general descriptors of urban built environment within the context of research. The characteristics under which measured attributes will be organized are density, diversity, scale, connectedness, enclosure, complexity, shape, incline, permeability and infrastructure. The term “attributes” will refer to the hierarchically lower level of more specific indicators that are grouped under these characteristics such as the height to width proportion of street spaces, average façade width on a street or percentage of visible sky from a viewpoint on a street. Attributes are calculated using some arithmetic or geometric operations on the most basic, quantitatively measurable features of the built environment which will be referred to as “properties”. Street segment lengths, building heights or building façade widths are examples to properties. The physical components that will be used to measure and evaluate walkability such as buildings, boundary walls, streets, trees and topography will be referred to as “elements”. Additionally, as part of the methodology to be presented in this section, 3d units representing the open spaces making up the streets are generated that will be referred to as “entities”, properties of which will also be used to calculate attributes contributing in the characteristics to be evaluated. Entities will be further explained in the following sections. All publicly accessible urban facilities and services will be referred to as "amenities" and include but are not limited to all kinds of retail stores, restaurants, cafes, bars, parks, playgrounds, public gardens, schools, sports facilities, co-working facilities, museums, theaters and hospitals.

4.2 Workflow

The diagram in Figure 4.1 demonstrates the steps of the study that will be elaborated in this chapter.

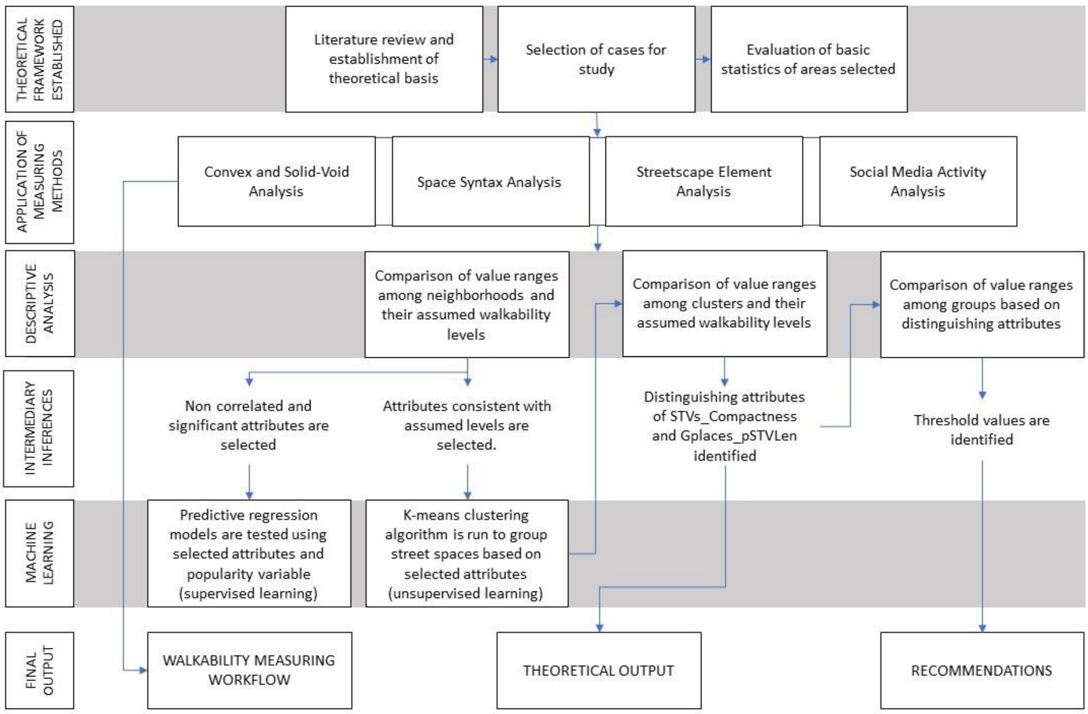


Figure 4.1 : Workflow.

In summary, following a selection of indicators through a literature review, a set measurable through morphology and street view imagery were determined. Through four case studies, these indicators were computed using attributes measured by Convex and Solid-Void models, Space Syntax analysis, streetscape element analysis, LBSN and LSS data analyses. Statistical analyses were performed and recommendations to inform urban design and planning processes were presented.

4.3 Meanings, Background and Categorization of Qualities

This section presents a list of characteristics and their contributing attributes that appear in human-centered urban design and walkability research, along with traditional and proposed methods to measure them. The proposed methods are the main subject of this chapter, and are based on 3d morphological analysis of streets, 2d morphological analysis of the street network, amenity locations present on open source map platforms and streetscape features documented through automated image processing of street view data. The reasoning behind the choice of these methods to acquire and analyze built environment data relies on two principles. Firstly, the proposed workflow in the thesis is aimed as a semi-automated and remotely applicable analysis method to any neighborhood for which the most commonly accessible urban information is available. This information includes the topography, in the form of point or isocurve data; building outlines which are available as either roof projection outlines or building footprints along with roof elevations or number of floors; block outlines; public and private amenity locations; and street view images. The majority of this data regarding the topography, buildings, plots and streets, is available from various resources from local municipalities to global data platforms and its availability to public through openly accessible online platforms is encouraged by governments through open data policies in many countries. Amenity locations are easily and freely obtainable from open map platforms such as Google Maps or Open Street Maps that are crowd sourced and therefore rapidly updated. Street view images are accessible through providers such as Google Street View or Bing StreetSide which also make application programming interfaces (APIs) available for their automated collection and processing. The second principle in the choice of the analysis methods is their relevance for street and neighborhood scale analysis. As explained in the previous chapter, walkability analyses in this scale are concerned with streetscape features that are difficult to measure without time consuming and costly on-site audits, which is a problem that this research aims to address through a detailed assessment of morphological attributes combined with remotely collected data about urban elements as well as amenities. The main idea is to facilitate a detailed yet practical analysis of the urban built environment characteristics for which acquisition, updating and feeding-in of data can be automated as much as possible.

A categorization of the attributes under characteristics is useful firstly for establishing their relationship with the existing literature and methods for measuring walkability. Secondly, it is necessary for acquiring a reduced set of attributes to facilitate a more practical means to measure walkability which is one of the aims of this study. Whether this is possible will be investigated in order to find the most significant attributes influencing walkability of the built environment. Thirdly, communicating the necessity, relevance and means of applying walkability as a criterion in the design and management of the urban built environment to decision makers is more practical through the use of over-arching, principle terminology more likely to be familiar than multiple specific attributes referred to by technical terms.

Brief definitions of the most commonly utilized built environment characteristics in walkability literature have already been presented in the previous chapter. In the current research, this categorization is used as a departing point to define a new categorization that incorporates primarily morphological attributes measured using a method called Convex and Solid-Voids along with Space Syntax; streetscape elements and amenity information using open mapping and street view platforms in a way that is relevant for street-scale analysis. Table A.1 provides the list of attributes under this newly proposed categorization with explanations on how the characteristics and attributes are commonly measured and how the current research measures them. This is followed by an in-depth description of the characteristics as they appear in literature and differences in how they are utilized in the current study. The reasoning behind the omission of some characteristics that commonly appear in literature are also explained. The means for data acquisition and methods of analysis applied to this data will be presented in detail in the following sections.

The “unit area of analysis” frequently referred to in the Table A.1 is the selected unit of area or points of reference utilized for the analysis of attributes in the urban environment. There are various different units utilized in walkability literature such as the floating catchment area within a distance per point, a statistical subsection, a census district zone, a block group, a taxable lot area, a grid cell area or a building center point. The unit area of analysis proposed and utilized in this research is the total area of street space throughout the length of street segments bounded by the terrain, buildings and other vertical urban limits such as garden walls, gates, balustrades and hedges. These units are entities auto-generated through the Convex and Solid-Void models and called Street-Voids. The term "continuous street space footprint area" referred to in Table A.1 refers to the footprint area of these auto-generated entities. Details of this methodology is explained in the next section.

Density, a rather broad concept that comes to indicate frequency or concentration of buildings, built square meters, commercial functions, registered population or human activity within a unit area of space; is considered one of the most significant factors affecting how walkable an urban area will be. This comes from the understanding that the more people reside, work or occupy an urban area, the more likely that there will be amenities and services that facilitate activity on the street; density makes it more feasible to build infrastructure such as sidewalks and invest in public transportation that encourages walking, and unlike suburban neighborhoods where density levels drop, destinations will be closer to each other making them easier and more convenient to access on foot, rather than by car.

Jane Jacobs (1961) emphasized the importance of population density as one of the four main rules she established as necessary to create an active street life. Jan Gehl (2011) focused on the necessity to assemble people and activities rather than dispersing them in order to stimulate more interaction and therefore draw more people and activities to public spaces. For both authors, the frequency of visual and physical access to streets carried utmost significance in connecting the public and the private space, thus fostering a vibrant social life among the residents as well as the visitors in urban neighborhoods. The number of people on the street has been identified as a contributing factor to attracting even more people to the streets by making them more imageable (Cullen, 1961) and visually complex (Ewing & Handy, 2009). Density has come to be considered one of the primary indicators of walkability as one of the "D" variables along with diversity, design, destination accessibility and distance to transport (Ameli et al., 2015; Cervero & Kockelman, 1997; Ewing & Cervero, 2001, 2010; Ogra & Ndebele, 2013). Several measures including population, building footprint and total floor area, dwelling units and employment per unit area have been identified as indicators of walkability and were commonly grouped under the "Density" variable (Ewing & Cervero, 2010; Vale & Pereira, 2016). Density contributes to walkability not only by increasing the attractiveness and social interaction accommodated by urban environments, but several services including public transportation becomes more efficient and convenient to provide to people living within closer proximities.

Even though density is considered such a significant contributing factor for walkability, it's relationship with urban form have been questioned in literature (E. R. Alexander, 1993; Forsyth, 2003). One reason for this is the several possible distributions of the same built floor area within the same unit area of analysis resulting in the same proportion of built floor area to unit area. To clarify this issue, Pont & Haupt (Pont & Haupt, 2010) argue that three density indicators of intensity (Floor Space Index), compactness (Ground Space Index) and network density (N), when combined together, can describe the built environment density distinctly for varying urban morphologies. They furthermore argue that whether dictated by individual, physical, collective or societal contexts, these three measures constitute the definitive constraints of urban form when combined. A density measure for Pont & Haupt (2010), the ratio of total network length per base area of study (Network Density), along with density of network intersections and link-to-node ratio are more commonly referred to as indicators of "Connectivity" (Frank et al., 2005; Leslie et al., 2007; UN Habitat, 2013; Van Dyck et al., 2010) which is also one of the most widely utilized measures in walkability research. In the present research, connectivity and node count attributes from the Space Syntax method are utilized instead, and categorized under the characteristic of Connectedness, under which additional street network attributes measured using the Space Syntax method are grouped. Therefore, node density is not regarded as part of the "Density" characteristic. The attributes that are used to measure the Density characteristic in this study are building area density, floor area density and density of amenities per unit area of street space. While traditional methods require census and land use data to measure this characteristic, this research uses morphological data of the building footprints, number of floors (derived from the height of the buildings and estimated floor heights if not known) and amenity locations drawn from Google Maps. The reason for this is easier accessibility and higher reliability of the building and amenity data through openly accessible databases compared to census and land use data.

In traditional walkability research, density is part of larger scale attributes and is sometimes used in street-scale analysis as a controlling variable. Within the current study, it is considered relevant to measure for each street segment due to being not only a potential indicator for urban activity and liveliness, but also being measurable through urban form and modifiable through strategic planning decisions. As a recent example among several cases in urban centers around the world, FAR increases have been utilized politically by municipal planning offices to encourage urban regeneration of neighborhoods around Caddebostan neighborhood of Istanbul.

Diversity is another attribute closely related with the pedestrian experience of urban streets, and is one of the widely accepted "D" contributors in several walkability indices developed (Cervero & Kockelman, 1997; Ewing & Cervero, 2010; Saelens & Handy, 2008; Vale & Pereira, 2016). More commonly measured using land use information and also referred to as "Land Use Mix", it is calculated by percentages of single-family buildings, residence dwellings, number of available activities or area occupied by activities. Diversity appears in larger scale walkability analysis and is sometimes used as a controlling variable in street-scale analysis. In larger scale walkability indices, Diversity is measured based on the multiplicity of different uses and functions on a street. However, this thesis investigates the possibility that there are also a number of morphological properties that contribute to the diversity perceived in a built environment meaningful to measure in a street-scale walkability analysis, as this will affect the attractiveness, interestingness and therefore the walkability of a street. It is also considered relevant for street-scale walkability analysis, as both morphological and amenity attributes contributing to diversity are considered within the decision capacity of municipalities and are therefore modifiable through urban design legislation in favor of more walkable streets.

Another principle Jacobs (1961) defends for lively and walkable urban streets is for buildings on a street to be diverse in terms of their age, condition and use. Within this research, in addition to the number of various commercial amenities encountered on a route, the variation in a number of physical attributes of the streetscape are also measured. Along with the number of buildings per 100m, a variance in the buildings' heights is considered to affect the diversity of the built streetscape. Lehnerer (2009) refers to the undesirable uniformity of building heights as the "Skyline wall syndrome" and explains it with the concept of "Economic Height". According to the author, due to all high rises built around the same time having similar economic limitations, their shapes, sizes and specifically heights tend to be the same and therefore a variance in skyline is lost (Lehnerer, 2009), which he refers to as an aesthetic problem. Besides measuring the morphological variation among the street elements such as buildings and walls, the variation within the 3d entities generated by the Convex and Solid-Void models utilized to evaluate the morphological attributes of the urban streets are also calculated. Of these entities, the Convex-Voids are units representing continuous chunks of the street spaces. This method and its entities will be explained in detail in the next subsection.

Complexity: Ewing and Clemente (2013) attribute the imageability and perceived complexity along a street to several properties related to the shapes, sizes and colors of the buildings on a street and identify number of buildings per 100 meters, number of buildings with non-rectilinear silhouettes and number of primary and secondary colors per building as indicators. A way of quantifying visual variation based on the assumption that change awakes interest and captures attention, this information is difficult to retrieve without on-site audits or currently available automated processes. On the other hand, the level of articulation by which this research refers to fragmentation of the building and wall facades, sight lines and routes along a street are measurable morphological properties that increase the level of perceivable complexity on a street. Several authors emphasize the significance of an increased detail, or high level of articulation perceivable in more attractive and interesting streetscapes (Hansen, 2014; Kolsova, 2017) and also encourage this in design as a means to better relate to human scale (City of New York, 2013; Ewing & Handy, 2009). The level of articulation of the physical form of the street wall is also likely to imply a higher number of built units and therefore a possibility to accommodate a higher number of varying uses, increasing the potential for diversity on a street. The number of unique building facades encountered per unit length of a street, which also contributes in diversity, is accepted in various studies as an attribute that makes streets more attractive (Harvey et al., 2015) and visually complex (Ewing & Handy, 2009) and therefore more interesting for pedestrians. Gehl (1987) states that façades should be narrow in width, allowing for as many shops as possible in the shortest possible street distance. Narrow facades also mean more doors and therefore more visitors per street length and a higher potential for the assembly of events (Gehl, 1987). This is also in line with Jane Jacobs's famous theory of "Eyes on the Street" which encourages more windows and doors facing a street in order to make it safer for the pedestrians (J. Jacobs, 1961). Gehl (2011) supports this principle with traditional and contemporary examples of Siedlung Halen in Bern and Java, Borneo and Sporensburg Islands in Amsterdam. Seattle is another city that has adopted the law that limits the shop fronts to be no more than 1.5 times the width of their neighboring shop fronts and based on the same principles while New York City has limited the maximum length of building façade to 56m in its R4 Residential District (Lehnerer, 2009). Stamps (1999) proposes geometric evaluation methods to assess façade articulation, surface complexity and silhouette complexity and correlates them with visual preference of facades, finding surface complexity to be the most significant of these factors to effect preference.

This thesis measures façade articulation levels as part of the character of Complexity, and variation in morphology that includes changes in building height and façade dimensions as part of the character of Diversity, linking physical variation with a potential in variation of function and use.

(Human) Scale: The physical measurable dimensions of the elements making up the built environment are naturally highly descriptive of urban morphology. The width and length of streets, heights of buildings and walls surrounding and defining the street space or the "urban room" constitute the primary attributes concerning this characteristic. The sizes of open urban spaces have been debated upon often in the urbanist literature. There seems to be a consensus on the negative effects of too wide or too large open spaces due to their dispersing effect. Gehl (2011) talks about the thinning of outdoor activities due to over-dimensioned open areas around detached single-family houses and functionalistic apartment blocks. For him, this is closely related to maximum distances that allow people to see, recognize and carry out conversations with each other (20-30m), recognize events (20-100m) and the distances they will be willing to walk (400-500m). While walking comfortably on a street requires space and sufficient sidewalk width, streets wider than 20-30 or 40m and plazas wider than 40-50-60m disperse people and cause thinning of activities. Thus, streets need to be wide enough to be comfortable but narrow enough to offer rich encounters (Gehl, 1987). He mentions the traditional distance of two to three meters between market stalls being ideal for trade and clear visibility of merchandise on both sides and pedestrian traffic with the example of Venice marketplaces (Gehl, 2011). Lynch and Hack (1984) suggest that an ideal open space in the urban context is 25m wide and the width of good urban spaces is rarely over 110m. Lehnerer (2009) suggests that one of the main reasons for the unattractiveness of streets for pedestrians in

Houston Texas is their width: the main streets are 30m wide and the residential streets 18m. Also, within the quantitative walkability assessment indices, street width have been used as one of the indicators deemed to contribute negatively to the walking experience (Harvey et al., 2015).

The heights of buildings have been accounted for taking away from of the pedestrian experience as well, both due to micro-climatic effects and working against the sense of human scale, especially in the case of high-rises. Gehl suggests that high-rises are unfavorable for climatic conditions as they direct high winds downwards and low buildings provide longer summer conditions as opposed to tall high-rises (2011). Also due to easier access from the inside and the outside, or the "flowing" being easier and more spontaneous, low buildings facilitate an abundance of stationary activities around their entrances and along their facades that high rises don't, which Gehl deems necessary for lively streets (2011). For different authors, buildings over six, four and even three stories are considered too high to relate to the human scale (Ewing & Handy, 2009). Based on these assumptions and the opinion of an expert panel, Ewing & Handy (2009) include the building height as one of the indicators that negatively influence human scale which is one of the five primary measures of their walkability index. In one walkability index, building height is scored as excellent, good, poor and bad for high-rises, apartment blocks, townhouses and bungalows respectively (D'Alessandro et al., 2015).

The lengths of streets and blocks have been subject of interest for authors investigating successful built environments as well. Jacobs advocated shorter block lengths (1961) to create the "lively street corners" necessary for vibrant neighborhoods. Lehnerer (2009) proposes the rule to increase "population ratio to street length" for the planning of better cities. He points out the unsuccessful case of Houston where street crossings were designed to be at least 180m apart from each other and endorses the rule for the lengths of streets to be as short as possible, which was adopted in a research for an urban design generation tool developed at ETH Zurich (Lehnerer, 2009). Long and uninterrupted sight-lines which result from long block lengths are also identified as indicators negatively contributing to the sense of human scale on a street in the study of Ewing and Handy (2009).

Enclosure: The proportion of building heights to the width of a street is commonly utilized as a measure of enclosure, openness or spaciousness which refer to how well the boundaries of an urban space is defined or how much it feels like an outdoor-room. According to Ewing and Clemente (2013) the increase in the ratio of height to width of streets increase the feeling of enclosure and enhance walkability. They refer to several authors who have defined ideal values for this ratio such as 1, 0.5 or greater than 1:6 or 3:2. Their study also puts forward an indicator that quantifies the proportion of visible sky from various locations on a street, contributing negatively to the measure of enclosure. Harvey et al. (2015) find in their study on walkability that tall and narrow streetscapes are perceived to be safer than short and wide streetscapes. A line of buildings with facades lining up to constitute a wall-like boundary of this outdoor-room, or street-wall continuity also contribute to this measure. Building set-backs larger than 3-4 m add to the perceived width and increase the distance between pedestrians and activities around the surrounding buildings that constitute potential for social encounters (Gehl, 1987). In his book “The Happy City”, Montgomery (2013) talks about wide street setbacks discouraging the interaction between the public and the private, separating them and making the streets feel vast, empty and less safe. Lehnerer (2009) points out the law in New York City established by the Urban Design Group which required the buildings to stand directly on the edges of their parcels as a solution against the large setbacks caused by high-rises receding their ground floors to create public plazas following the 1961 zoning ordinance. He suggests a similar rule for the recent development of the large areas around the Zurich train station, proposing "a fixed percentage of the boundary of the outer envelope has to be in contact with future development" especially in the lower sections of the building to avoid excessive setbacks of the architectural volume. As supported by all the literature focusing on the significance of enclosure in helping foster more lively and safer feeling outdoor spaces, many studies assessing quality of the built environment and its relationship with walkability have utilized measures of enclosure and developed means to evaluate this indicator (Harvey et al., 2015; Kaya & Mutlu, 2017; Kolsova, 2017; Lindal & Hartig, 2013; L. Yin & Wang, 2016).

Connectedness: Commonly referred to as “Connectivity,” this indicator is referred to as Connectedness in this thesis to distinguish it from Connectivity which is the Space Syntax attribute. Frank et al., (2010) define this indicator as a proportion of true intersections where three or more streets intersect, with the total block area studied and utilize it as one of the four indicators of their walkability index along with residential density, retail floor area ratio and land-use mix. Used as a more general term to refer to how connected a street network is, this indicator is based on the Space Syntax theory developed in the 1980s (Hillier & Hanson, 1984) which advocated that the configuration of a street network influenced human movement. Since pedestrian movement almost completely follows the street configuration in an urban environment, calculating how accessible destinations are, via the routes possible in a street network has been used as one of the primary means to assess walkability since the earliest research on the subject. There are a number of indicators that the current Space Syntax method and tools can measure. In one study, Choice, Integration and Connectivity have been found to have the strongest influence on pedestrian movement (Sharmin & Kamruzzaman, 2018). Additionally, Özbil et al. (2015) found that Metric Reach, which measures the total length of street segments accessible from a segment within a given buffer and Directional Reach, which is the total length of street segments accessible from a segment within a limited change of direction, were also highly influential on walkability. Along with these indicators, Angular Connectivity, Node Count and Total Depth are also measured as part of the Connectedness characteristic in this thesis. The original Space Syntax theory defines Connectivity as the number of segments immediately connected to a street segment and Node Count as the total number of street segments that connect a street segment to all others in a street network (Turner, 2004). This indicator, in fact, is commonly used in walkability research as the count of street intersections within a buffer area. Detailed explanations of utilized street network analysis indicators are available in Table A.1 and the Network Analysis section.

Shape: This measure is concerned with the shape of open spaces that are part of the assessed street network, both in the form of public squares as well as chunks of street spaces. These chunks are generated through the compartmentalization of the whole street space by the Convex and Solid-Void method utilized. The method allows for a homogenous analysis of urban space, without the need for preliminary designation of labels or a classification as street or square, but through the indicators grouped under the characteristic of Shape, making it possible to detect more square-like or street-like attributes. This provides an advantage in terms of the practicality of analysis: no additional semantic labeling is required to be linked with the 3d geometric model of the built environment fed to the Convex and Solid-Void model; furthermore, open spaces like squares can be distinguished from streets through evaluating these results without prior knowledge, purely based on their morphology. Additionally, the evaluation of smaller compartments, namely Convex-Voids that the space is divided into, allows for the evaluation of more street-like spaces in smaller chunks, which are analyzed for how compact or square-like they are. The three indicators utilized which are squareness, compactness and perimeter per area look at the ratios of the smallest bounding square to the footprint area, the perimeter of the largest inscribed square to the perimeter of the footprint and the total perimeter of the footprint to the footprint area of the spatial unit that is analyzed respectively.

These indicators are not common in walkability literature. Walkability assessments of urban environments usually focus on streets and street networks as the majority of the activity of walking takes place along streets rather than squares, which bring about their own body of research, as activity in these spaces tend to differ from destination-oriented walking, with the addition of stationary activities and social interaction. The morphology of these spaces also diverges from that of streets with changing proportions in plan and cross section as well as the addition of streetscape elements like landmarks, landscape elements, street furniture and street art. In some cases, storefronts, restaurants and cafés find room to extend into the square displaying their goods or providing outdoor seating and service to their customers directly on the square. Several studies exist focusing on the design of these public urban spaces and its link with how actively they are used, in an attempt to better inform their design and management processes (Charlton, 2011; Childs, 2004; Martín & Guayo, 2013; Marušić, 2010; University City Distirct, 2013). Nevertheless, the geometric proportions of both streets and squares are studied, most commonly to quantify levels of enclosure therefore taking into account the street or square width to average height of surrounding buildings. Studies on thermal comfort in open public spaces also utilize 3d proportions to simulate the influence of weather conditions and shading in open public spaces.

Incline: While it is undeniable that the slope of a walking route, or the ratio between the change in elevation and the projected length of the route affects the pedestrian experience, it has commonly been ignored in walkability measuring research (Daniel & Burns, 2018) most likely due to challenges in incorporating the 3d terrain information in the analysis methods. One survey found that slope of a street is more often taken into account in bikeability research than walkability studies (Vale et al., 2016). On the other hand, a study focusing on the difference between the pedestrian catchment areas that are calculated as a buffer covering the areas that can be accessed on foot, from a point, within a time or distance (typically 400m or 5 min walking), with and without taking into consideration the slope of the streets on a hilly terrain, found 20% drop in the walkability calculated when slope was taken into consideration (Daniel & Burns, 2018), and other studies found negative correlation between slope and walkability (Moura et al., 2017; Özbil et al., 2015). A 8.33% slope is considered safely accessible for ramps by American Disabilities ACT Standards (United States Access Board, n.d.) and paths around a similar slope begin to impede walkability.

The cases studied in the current research are from relatively flat neighborhoods from Istanbul but hilly neighborhoods from Lisbon. Along with the average slope percentage, the maximum change in elevation and the variation in the slope levels within each unit area of analysis are proposed as indicators and measured for each case.

Permeability/Transparency: This measure is concerned with the level of visual and physical access between buildings and street spaces. The liveliness, interestingness, attractiveness of a street, and even the feeling of safety when walking on a street have been linked to how much human activity is or potentially can be accommodated by the buildings on that street, as well as how visually and physically accessible they are to pedestrians. Jacobs (1961) championed the visibility of the street from windows as a means to provide safety to the street dwellers with her "Eyes on the Street" theory, that is facilitated by diversity of uses and thus varying hours of active use for buildings as well as proximity of building facades to the sidewalk. Based on this theory, a negative correlation between inter-visibility between buildings and the frequency of residential burglaries were found through empirical research (Lopez & Van Nes, 2007). Beirão & Koltsova (2015) found positive correlations between the permeability and observed liveliness of streets in cities of Lisbon, Moscow and Zurich. They have used permeability as the unifying term for the two characteristics of streets which are: the density of entrances and their level of exposure to pedestrians or territorial depth along a street. In walkability literature, the transparency measure developed to assess urban design qualities (Ewing & Clemente, 2013; Ewing & Handy, 2009; Ewing et al., 2006) have been commonly referred by researchers studying means to measure how urban street-scale built environment qualities influence pedestrian behavior.

In the current research, this characteristic is also proposed to be linked with the characteristics of Diversity and Complexity, as the density of entrances on a street can be expected to increase with the number of buildings per 100m and even if not a direct consequence, the increase in articulation of 3d spatial geometry is likely to account for an increase in this proportion.

Infrastructure Quality (and Maintenance): This indicator refers to the elements on a streetscape that have influence on the pedestrian experience which can be considered a part of the infrastructure of an urban environment. In literature, a loosely bounded range of elements including sidewalks, marked pedestrian crossings, street furniture and lighting, trees, pedestrian signals and islands and quality of intersections in term of how pedestrian friendly they are have been referred to as part of infrastructural measures (Forsyth & Southworth, 2008; Saelens & Handy, 2008; Vale & Pereira, 2016). Infrastructural elements measured as indicators of walkability within the current study have been selected based on their significance in walkability literature as well as their measurability using automated means of data gathering and analysis. These elements are street trees, furniture and sidewalks that are considered to have a positive influence on walkability. Cases of demolition, abandonment and calamity that in fact concern maintenance will be considered as consequences of infrastructure-related shortcomings and that negatively influence walkability. Presence of indicators of motor transit on a street such as cars, other vehicles and traffic have also been included under this characteristic, as the regulation of traffic and parking are also considered to be facilitated through infrastructural interventions.

Some measures that have been included in other walkability evaluations but that are not part of the attributes and characteristics used to assess walkability in this research are accessibility, distance to transit and demographics in the larger scale and imageability, various sidewalk qualities, the existence of street lighting, shading capacities of trees, existence of parking lanes along a street, ages of buildings or existence of historic buildings, intensity of traffic, noise, protection from traffic or design or convenience of crosswalks in the street and neighborhood scale.

The reasoning behind the omission of larger scale indicators is the specific focus on street-scale characteristics. For the current scale of analysis for which the measures are developed and the cases are tested, accessibility and distance to transit does not make sense as the geographical extent of the selected streets cover an area within a 5 minutes walking distance from end to end, making the variation of these values insignificantly small to measure. Demographics, which is not a built environment characteristic but is sometimes utilized as a control variable as it tends to influence the urban walking behavior, is not utilized as part of walkability measures in this research. However, the population densities of neighborhoods were taken into consideration when choosing study areas. The reason for the omission of demographics in the measures is that demographic data is not considered to be a frequently updated and reliable form of information; which this research adopts as a principle in the selection of data to be utilized. It should, however, be incorporated as the census collections methods are developed to become more efficient and reliable all over the world.

The primary reason behind the omission of the attributes concerning smaller scale walkability assessments in this research is similarly a lack of access to up-to-date and reliable data, especially since one of the main goals of this study is to eliminate the need for on-site audits and the resources they require. It is not surprising that one such attribute, the sidewalk quality, among the many streetscape attributes listed above, is one of the most commonly studied in walkability research. Sidewalks mark off the street spaces reserved for pedestrians in a motor-vehicle dominated world and determine the quality of the walking experience to a great extent. Even the existence of sidewalks has been linked with improved walkability but their width, coverage and quality of material also have an impact on how comfortable streets are for the pedestrians (Ewing & Cervero, 2010). A recent study investigating the relationship of the streetscape characteristics with the perceived qualities of the built environment found positive correlations between the existence of sidewalks on Google's Street View images and the streets' perceived liveliness (Zhang et al., 2018). Insufficient widths make it hard for pedestrians to walk in groups, support the elderly walking arm in arm, push strollers, carry along luggage and other loads. They hinder safety and perception of safety on streets with heavy or fast traffic by forcing the pedestrian to walk closer to the car lanes. Sidewalk surface material is also determining for the comfort of walking. Broken, uneven or badly maintained sidewalk surfaces make the streets difficult to use for the elderly, young children, wheelchaired, people pushing strollers, carrying luggage or women with high heeled shoes. Sidewalk surfaces that become slippery during rainy weather or at subzero temperatures become especially dangerous for these groups of pedestrians. Special treatments with texture changes or other accessibility design principles need to be incorporated into the design of sidewalks to guide the visually impaired. The height of the sidewalks (or curb reveal) determines how easy they are to step on and off from public transit vehicles such as buses and trams, and the existence and slope of ramps at street crossings provide easy access for the disabled and the elderly. In this study, only the existence of sidewalks on street sides were inspected and utilized as part of indicators, as it was possible to automate the retrieval of this information through computer vision analysis of Google Street View images, but as more detailed urban data becomes publicly accessible, information regarding these various sidewalk qualities should also be included as part of walkability measures.

4.4 Morphological Analysis

References to formal characteristics of the built environment appear frequently in human-centered urbanism literature as well as in studies focusing on walkability. Certain morphological attributes are referred to as directly affecting the pedestrian experience such as those measured by Space Syntax analysis of the street network or 3d morphological properties such as average building heights, street widths or block sizes. These are commonly measured in calculating walkability scores as part of indicators such as Connectivity, Accessibility, Comfort or Design in walkability literature. Some morphological attributes on the other hand, are results or reasons of phenomena closely related with walkability. One example to such phenomena is Density, which is represented with and measured using several different attributes within walkability research, including population data or proportion of residential or commercial built square meters to the area of analysis. Population density affects walkability due to reasons including people on the streets attracting more people to go out on to the streets, public services being more efficiently delivered to areas with higher densities as well as commercial amenities being attracted to higher densities due to increased demand. While one way of measuring population density is to use census data, the morphological expression of density in the form of built square meters for residential, public and commercial functions can reveal more information in terms of how the urban built environment is used. Especially when higher level of detail is explored as is in the street and neighborhood scale measures studied in this thesis, urban form becomes a relevant evidence for measuring density. The relationship between density and urban form has been studied extensively. In their dissertation, Pont and Haupt (2010) provide literature background regarding the investigation of the relationship between density and urban form and present a method to measure density, that is able to capture several design typologies based on purely morphological attributes of the built and unbuilt spaces of the urban fabric. Another example to a walkability related characteristic that can be inferred though morphology is diversity. As have been discussed in detail in the previous section, morphological variation as well as the level of articulation or granularity in the built environment may point to a diversity of uses for buildings. The various street typologies such as passageways, squares, residential streets, commercial streets, highways, boulevards etc. can be detected through their morphology if such information is unavailable. This thesis takes on the position that morphological analysis can help evaluate several such qualities closely related with street-scale walkability which will be especially useful especially in areas where comprehensive and accurate data sets in the required detail and scope are unavailable through local administrations or open platforms. Morphological information of urban environments, on the other hand, are becoming more accessible and accurate as open mapping platforms improve in parallel with remote sensing and image processing technology.

Already presented as groups under walkability-related characteristics (Table A.1), here we lay out the morphological and other streetscape attributes as well as their proposed measuring methods and intermediary attributes computed measuring them. The two methods of morphological analysis to be utilized that are Convex and Solid-Voids and Space Syntax analysis use data on streetscape elements easily obtainable in GIS format from municipalities or open data sources. These are topography, building footprints, building heights or number of floors, footprints and heights of other urban limits such walls and fences, and road network lines. This data is already informative of several aspects of the built environment. A 3d model that can be generated through automated processes can further help quantify many of these aspects objectively which the Convex and Solid-Void method primarily relies on. Going down to smaller scale in morphology, we also analyze data regarding streetscape elements such as the sidewalks, greenery, doors and windows as well as street furniture, this time using image analysis of street view images. While a finer-grained 3d streetscape model incorporating such elements would facilitate an even more accurate assessment of streetscape morphology, the automated generation of such a model requires well classified and consistent data that is currently unavailable for the majority of urban neighborhoods, as for the four areas to be studied as cases within this research. Instead, the existence of such streetscape elements is sought through auto-detecting these elements visually in Google Street View imagery. The Streetscape Attribute Analysis subsection elaborates on the method used to identify these elements used as part of the quantitative walkability measuring method proposed. Finally, street activity is measured by analyzing the frequency of instances where people were sighted in Google Street View imagery and distribution of geo-tagged social media posts. This method is explained in the Street Activity Analysis section.

4.4.1 Convex and Solid-Void models

Convex and Solid-Voids are 3d models that represent open spaces within the urban built environment as solid models that can capture multiple morphological attributes relevant for urban analysis (Beirão et al., 2015, 2014; Sileryte et al., 2017). Generated through a semi-automated workflow incorporating GIS, a 3d CAD model and a visual programming environment, these models compartmentalize the urban architectural void and allow for its study as field, network and object entities. Convex and Solid-Void models were extended and further developed to measure walkability-related urban characteristics as part of this thesis research. Focusing on street segments most suited to the subject of study, the spatial units are aggregated to represent street segments, where open spaces are treated as parts of network entities.

Five primary entities have already been introduced within previous Convex and Solid-Void research: Convex Spaces, Convex-Voids, Solid-Voids, Facades and Flows (Čavić et al., 2017). A sixth is proposed in this thesis as Street-Voids.

Convex Spaces (Figure 4.2) have previously been defined within the Space Syntax methodology (Hillier & Hanson, 1984) as entities to represent and analyze urban space. Fattest compartments of spaces are outlined on an urban plan based on the description of convexity in mathematics, which requires that a straight line can connect any two points on the outlining curve without intersecting itself.

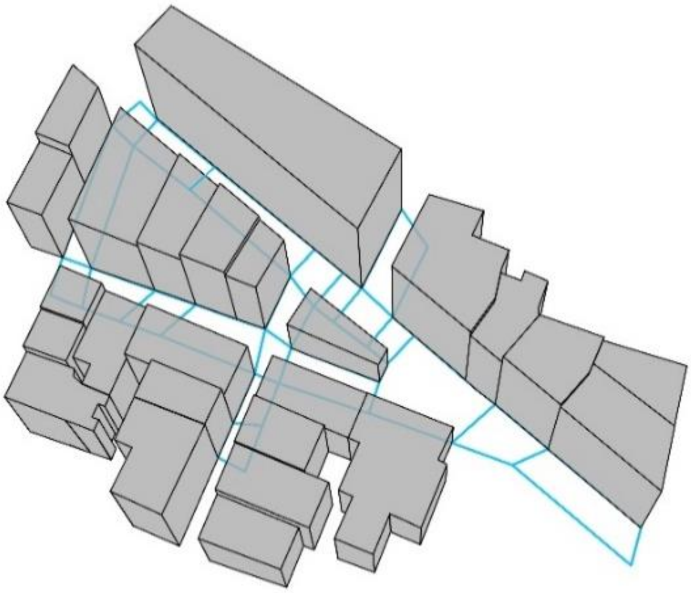


Figure 4.2 : Convex Space.

The Convex Spaces of the Space Syntax method have been criticized for lacking an automated method for their generation and ignoring three-dimensional information regarding the urban open spaces. Addressing these issues, 3d-informed Convex Spaces were introduced as part of Convex and Solid-Void methodology (Čavić et al., 2017) as 2d representative entities capable of incorporating 3d-geometric and additional information regarding the surroundings of the urban open space. Within this methodology, Convex Spaces are auto-generated in a 3d urban model using horizontal limits (topography and the overhangs horizontally delimiting urban space), vertical limits (all kinds of vertical **planar limits** delimiting urban open space walls, bushes, hedges, fences and **volumetric limits** which are most commonly buildings) and **implicit limits** (visual cues such as changes of building height on one side of the street which nevertheless affect the compartmentalization). A triangular mesh is generated in the 3d model delineating the open space defined by these boundaries and the triangles are merged to form unique Convex Spaces based on user-defined parameters that are horizontal and vertical convexity thresholds and superiority function. Convexity thresholds are the minimum allowed value for the proportion between the area of the convex space and the area of its convex hull in plan and section, and the superiority option defines whether a triangle should be a part of the Convex Space that is fatter and closer to a square in shape or fatter and more compact. Here, "..fatness is a radius of the biggest circle inscribed in a 2D polygon; compactness is a ratio between perimeter of a polygon and perimeter of a circle of the same area; squareness is a ratio between area of a polygon and area of its smallest bounding square.” (Sileryte et al., 2017). Convex spaces are 2d entities, however, they are not planar since they lay on the 3d mesh representing the topography.

In addition to Convex Spaces, related Façade and Flow entities as well as Convex-Voids and Solid-Voids are generated through the same automated procedure, allowing for the analysis of multiple morphological attributes of open urban spaces.

Façades (Figure 4.3) are all the planar components of the vertical limits surrounding a Convex Space.

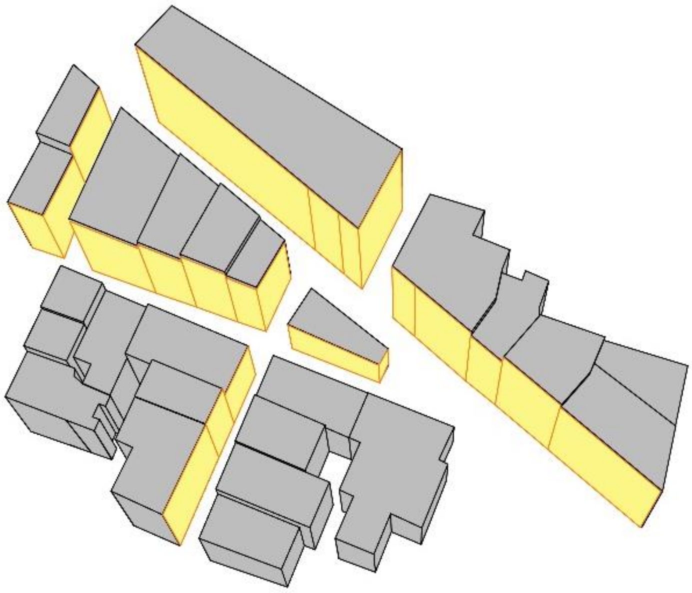


Figure 4.3 : Facades.

Convex-Voids (Figure 4.4) are 3 dimensional representations of urban open spaces, created through the extrusion of the Convex Spaces based on a function essentially calculating a weighted average (WAv) height of the surrounding vertical limits, the parameters of which can also be determined by the user.

This height value is adjusted through formula 4.1 provided below (Beirão et al., 2015), so that the transition effect from wider or narrower open spaces to their neighbors are also accounted for. Narrow and higher, therefore tunnel-like neighbors will cause a Convex-Void height to be increased, and wider and lower spaces will cause it to be decreased.

$$ {}_{cv}H_c = {}_{cv}H + {}_{cv}H_{adj} $$

${}_{cv}H_{adj}$: Height adjustment $(= {}_{G}H \times (3/\mathrm{Sqrt}(9 + A_g)))$
${}_{G}H$: Gross height correction value $((A_f - A_{fn})/P_s)$
A_g: Ground area of space
A_{fn}: Areas of neighbours' façades

(4.1)

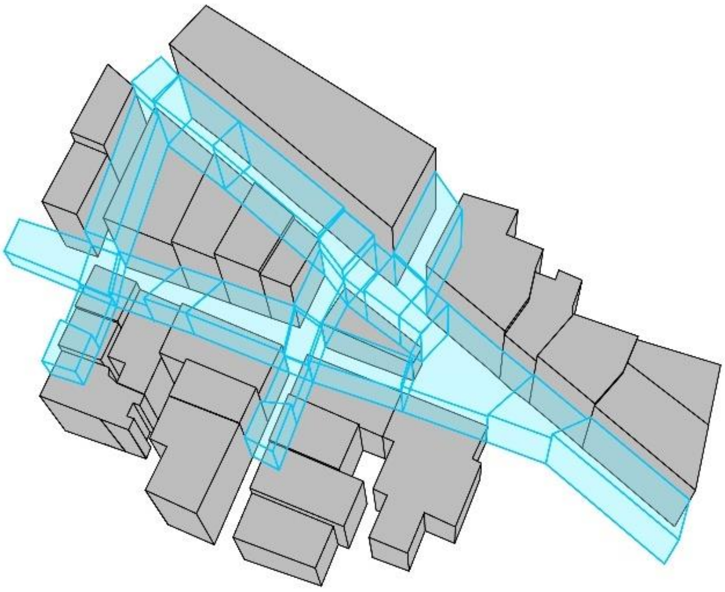


Figure 4.4 : Convex-Voids.

Flows (Figure 4.5) are the centerlines of the Convex Spaces creating a network going through all the open spaces.

Solid-Voids (Figure 4.6) are aggregations of the Convex-Voids grouped based on user-defined parameters regarding neighborhood relationship and continuity. These parameters are minimum proportion of lengths of overlapping edges, maximum deviation in angle of flows in plan and maximum deviation in angle of flows in section (in other words, inclination). While Convex Spaces are unique and do not overlap, Solid-Voids do. This means, one Convex-Void may be included in more than one Solid-Void. Also, Solid-Voids may overlap not only at street crossings, but also along streets (Figure 4.7). Solid-Voids constitute entities that allow for the aggregation of morphological properties within continuous wholes of open urban spaces. For example, the average of height or façade width values of Convex-Voids throughout a Solid-Void can be used as a single value to refer to when analyzing a part of a street or square.

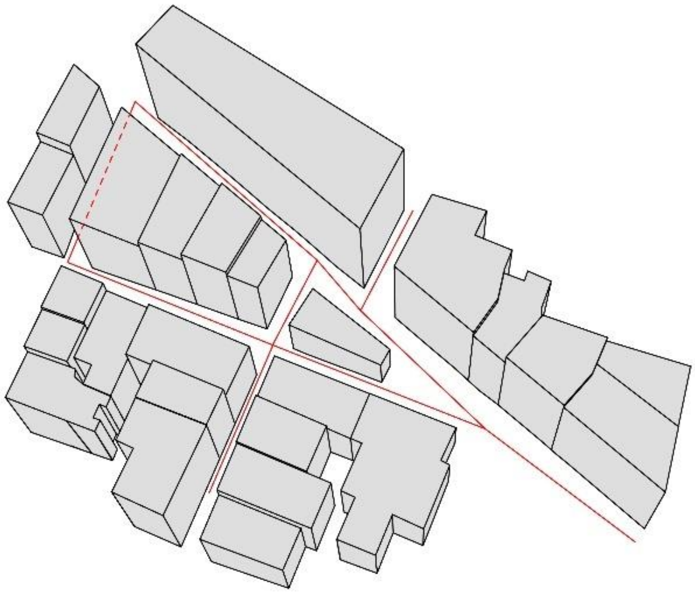


Figure 4.5 : Flows.

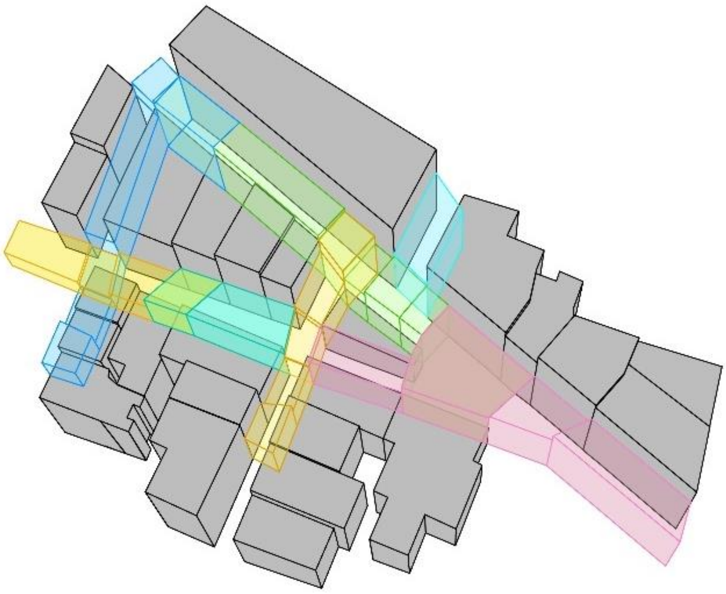


Figure 4.6 : Solid-Voids.

Street-Voids (Figure 4.8) proposed as new entities in this dissertation are also aggregations of Convex-Voids, however, they are based on street segments as defined by Özbil (2013), (Figure 4.9) and only overlap at street intersections (Figure 4.10). This was developed to address the problem of multiple Solid-Voids representing parts of the same street segment while partially or wholly overlapping, which makes it necessary to refer to several Solid-Void attributes regarding a single street segment.

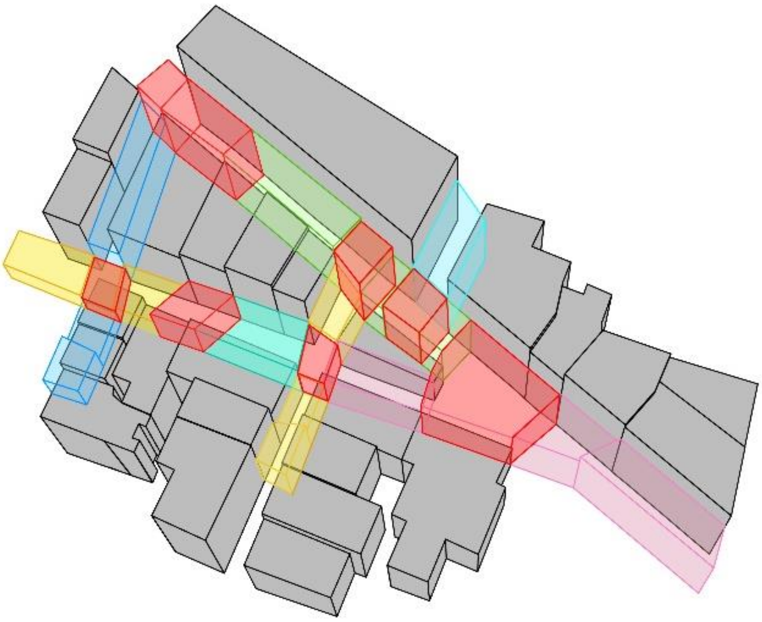


Figure 4.7 : Solid-Void Overlaps**.**

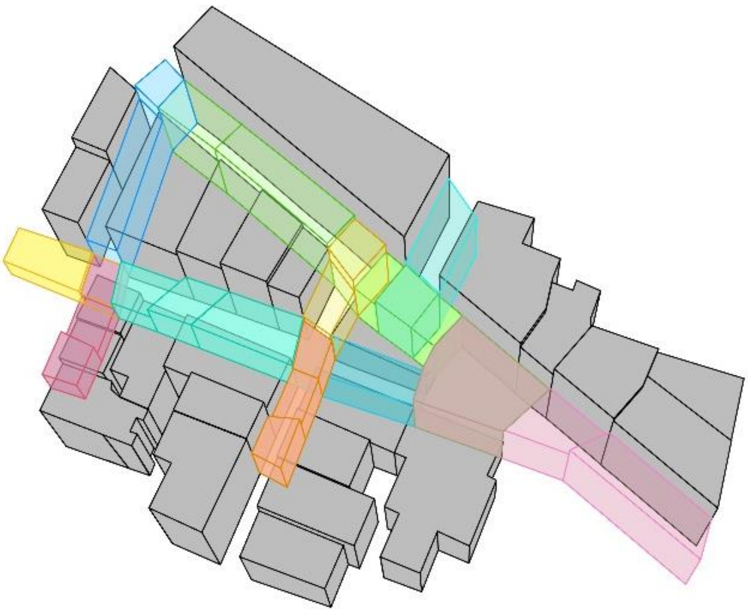


Figure 4.8 : Street-Voids.

Through a parameter that can be defined by the user, the street segments can be extended at the nodes allowing for the inclusion of spaces at street crossings as is the case in Figure 4.10.

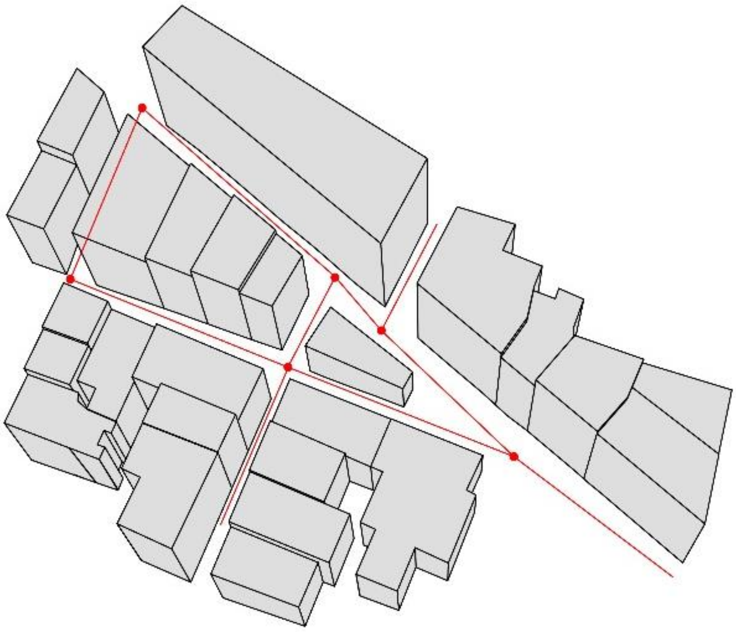


Figure 4.9 : Street segments.

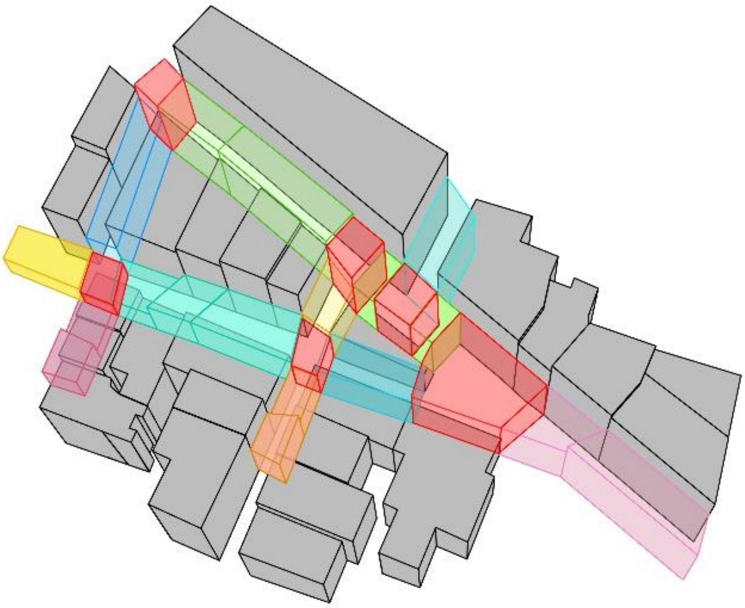


Figure 4.10 : Street-Void Overlaps.

Through the automated algorithm that generate these entities, several of their properties such as height, width, length as well as attributes such as height to width proportion, number of facades per 100m flow length, weighted average of lengths of facades per street segment can be calculated.

The primary set of properties measured for each type of entity and a set of morphological attributes deemed relevant for walkability that are measured per Street-Void as part of the walkability assessment workflow in this thesis are presented below

(Table 4.1). The Street-Void was developed and selected as a unit of assessment since it is able to capture the 3d-spatial qualities of a street segment, allowing for morphological attributes to be evaluated per unique street, also for combination with other analysis such as Space Syntax that uses the extent of street network within the same unit for analysis. The primary properties are not to be used as part of the final walkability analysis workflow but are necessary for the calculation of Street-Void attributes (Table 4.2).

The relevance and significance of these indicators for the proposed walkability analysis have been discussed more generally in this chapter and will be further elaborated through the interpretation of the measured results for the four case studies in the next chapter.

Table 4.1 : Property and attributes of primary entities.

Property/Attribute	Explanation	Formula
CS_ID	Convex Space identifying name	
CS_Area	CS footprint area (not projected)	
CS_Perimeter	CS perimeter (not projected)	
CS_Compactness	Perimeter of the circle with the same area as CS divided by perimeter of CS	√(CS_Area/(CS.Perim**2/4*pi))
CS_Squareness	CS Squareness	CS_Area/Area of bounding square
CS_Skyview	CS Sky View Factor	% of rays originating from CV center to a hemispherical surface that do not intersect with urban limits
CS_Elevation	CS center point elevation	
CV_ID	Convex-Void identifying name	
CV_Height	Weighted average of surrounding building heights	
CV_FacArea	Total area of surrounding facades	Facade1_Area + Facade2_Area + …
Fac_ID	Façade identifying name	
Fac_Height	Façade height	
Fac_Width	Façade width	
Fac_Area	Façade area	
Fac_HeightTWidth	Façade height to width ratio	Fac_Height/Fac_Width
F_ID	Flow identifying name	
F_Length	Flow length	
F_Incline	Flow slope percentage	(Elevation change/distance)*100

Table 4.2: Property and attributes of Street-Voids.

Property/Attribute	Explanation	Formula
STV_ID	Identifying name	-
STVs_Area	Footprint area of STV (not projected)	-
STVs_Length	Length of STV. Length of longest continuous street segment within an STV.	-
STVs_Width	Average width of STV. STV area divided by length.	STVs_Area/STVs_Length
STVs_Perimeter	Perimeter of STV footprint.	-
STVs_Height	Adjusted weighted average of heights of included CVs (see formula).	-
STVs_HeightTWidth	STV_Height divided by STV_Width	STVs_Height/STVs_Width
STVs_PerimTArea	STV_Perimeter divided by STV_Area	STV_Perimeter/STV_Area
FlowLengthTSTVArea	Total length of included Flows divided by STV area.	Flow_Lenght1+Flow_Length2+…/ STVs_Area
WAV_FlowIncline	Weighted average of slope of Flows within STV.	Flow1_Incline*Flow1_Length+ Flow2_Incline*Flow2_Length+…/ Flow1_Length+Flow2_Length…
STVs_NFacadesPerM	Number of surrounding Facades per STV length.	
WAV_FacadeHeight	Weighted average of building and wall façade heights surrounding STV.	Facade1_Height*Façade1_Width+ Facade2_Height*Facade2_Width+ …/ Facade1_Width + Facade2_Width…
WAV_FacadeWidth	Weighted average of building and wall façade widths surrounding STV.	$Facade1\_Width^2$ + $Facade2\_Width^2$+…/ Facade1_Width + Facade2_Width…
WAV_FacadeArea	Weighted average of building and wall façade areas surrounding STV.	$Facade1\_Area^2$ + $Facade2\_Area^2$+…/ Facade1_Area+Facade2_Area…
WAV_FacadeHeightTWidth	Weighted average of building and wall façade height to width proportions	Facade1_Prop*Facade1_Area+ Facade2_Prop*Facade2_Area+…/ Facade1_Area+Facade2_Area+…
STVs_Enclosure	Proportion of total Façade width to perimeter.	Facade1_Width+Facade2_Width+… /STV_Perimeter
STVs_ElevationChange	Change in elevation within an STV.	Elevation Max – Elevation Min
STVs_Compactness	Perimeter of the circle with the same area as STV divided by perimeter of STV	√(STV.area/(STV.perim**2/4*pi))
WAV_CS_Compactness	Weighted average of included CS Compactnesses per STV.	(CS1Compactness*CS1Area+ $CS2Compactness*CS2Area^2$ + …/ STV_Area

Table 4.2 (continued) : Property and attributes of Street-Voids.

Property/Attribute	Explanation	Formula
WAV_CS_Squareness	Weighted average of included CS Squarenesses per STV.	(CS1Squareness*CS1Area+ CS2Squareness*CS2Area + …)/ STV_Area
WAV_CS_Skyview	Weighted average of included CS Sky view factors per STV.	(CS1Skyview*CS1Area+ CS2Skyview*CS2Area + …)/ STV_Area
WAV_CS_Elevation	Weighted average of included CS Elevation values per STV.	(CS1Elev*CS1Area+ CS2Elev*CS2Area + …) / STV_Area
Cov_CSCompactness	Coefficient of variation of included CS Compactnesses per STV.	Sd(CS_Compactnesses)/ Avg_CS_Compactness
Cov_CSSquareness	Coefficient of variation of included CS Squarenesses per STV.	Sd(CS_Squarenesses)/ Avg_CS_Squareness
Cov_CSSkyview	Coefficient of variation of included CS Skyview factors per STV.	Sd(CS_Skyviews)/ Avg_CS_Skyviews
Cov_CSElevation	Coefficient of variation of included CS Elevations per STV.	Sd(CS_Elevations)/ Avg_CS_Elevation
Cov_CSDiameter	Coefficient of variation of included CS's largest inscribed circle diameters per STV.	Sd(CS_Diameters)/ Avg_CS_Diameter
B_p_STV_Len	Number of surrounding buildings per STV length.	# buildings/STVs_Length
Avg_Floors	Average number of building floors per STV.	#Floors_B1+#Floors_B2+../ #Buildings
Cov_NFloors	Coefficient of variation of building floor numbers per STV.	Sd(#Floors)/ Avg_#Floors
STV_BArea_p_STV Len	Total footprint area of surrounding buildings per STV length.	BArear1+BArea2+BArea3+ …/ STVs_Length
STV_BArea_p_STV Area	Total footprint area of surrounding buildings per STV area.	BArea1+BArea2+BArea3+ …/ STVs_Area
AV_BArea	Average footprint area of surrounding buildings per STV.	Barea1+Barea2+…/ #Buildings
Cov_BArea	Coefficient of variation of building footprint areas per STV.	Sd(BAreas)/ Avg_BAreas
STV_FArea_p_STV Len	Total floor area of surrounding buildings per STV length.	FArea1+FArea2+FArea3+… / STVs_Length
STV_FArea_p_STV Area	Total floor area of surrounding buildings per STV area.	FArea1+FArea2+FArea3+… / STVs_Area
AV_FArea	Average of floor area of surrounding buildings per STV.	FArea1+FArea2+…/ #Buildings
Cov_FArea	Coefficient of variation of building floor areas per STV.	Sd(FAreas)/ Avg_FAreas

A limitation of the current Convex and Solid-Void analysis model is not being able to account for horizontal limits, resulting in the morphology of under and overpasses, arcades and similar urban structures not being analyzed. Also, the generated entities are dependent on the detail available in the 3d model fed into it, and this model is generated based on the GIS and CAD files containing the information regarding the topography, building footprints, building heights or number of floors and the geometry of other urban limits like walls, fences, bushes and other barriers alike. If there is limited information regarding these elements, the model can only be built by simplifying this information. The 3d models for the four case studies in this research were generated by extruding all building footprints with a value of 3.5 times the number of floors from the projection of the center of gravity of the footprint on the 3d topography model. The walls and other linear urban limits were extruded 1.5 meters above the projection of the center of gravity of their footprints on the 3d topography model.

The Convex and Solid-Void method is still in the phase of development. The module accounting for the horizontal limits is to be completed; an additional entity named "Fragmented Voids" (Čavić, 2018) is to become a part of the method that is able to assess streetscape elements in more detail, considering elements such as street furniture, pavement materials and treatment or temporary elements that nevertheless affect the experience on a street; but most importantly, the method currently utilizing several steps that need to be performed in a CAD model, GIS model and a visual programming environment is to be simplified and fully-automated through Python programming and cloud computing. While the current semi-automated workflow allows for a lot of user input and the computation of unlimited number of measures that the user may generate tweaking the model in the visual programming environment, it is not intuitive and easy to use for someone not familiar with all of the utilized software. Nevertheless, the method has been tested with a group of students at the University of Lisbon's Design Computing Group's Summer Workshop in July 2018 (Ensari, de Klerk, Beirão, & Čavić, 2018), where students with beginner to no skills with the GIS and visual programming software environments were able to utilize the method with a few hours of training. Working in groups of two, they were able to analyze a small number of streets and interpret the results in terms of how morphology could be linked to vitality and walkability of streets.

4.4.2 Street Network Analysis

The software DepthmapX (Gil, Varoudis, Karimi, & Penn, 2015) and its plugin for QGIS was used for Space Syntax Analysis of the street network. Each segment within the study areas was analyzed together with its neighboring street network segments within 1200m 800m and 400m radius from their center of origin. These distances are commonly used to analyze ranges of 15, 10- and 5-minute walking catchment areas in a street network. In this study, 1200 and 800m radii analysis was used for an initial comparison of the four neighborhoods and 400m analysis radius (Appendix-E where results are aggregated per unit area of analysis) as part of the morphological analysis in explaining street activity. The measures utilized are listed with their meanings and explanations below (Turner, 2004).

Connectivity: Number of street segments immediately connected to a street segment.

Node Count: The number of all street segments passed through in the routes from a street segment to all others in the network.

Angular connectivity: Cumulative angle of all segments connecting to a street segment.

Choice: How likely a street segment is to be used within all the shortest routes connecting all street segments to all street segments within the given radius, in our case, 400, 800 and 1200 meters.

Integration: The normalized distance from any street segment to all other street segments in the network. It calculates how close each segment is to all the other segments.

Total depth: The total of all topological depths from any street segment to all other street segments.

In the process of analyzing the given street segments, the software utilized splits all segments of the street network at intersections *and* corners, even if the street does not intersect with any other at that corner. This means, unlike the street segment we use to generate our Street-Void unit for all other analysis, the Space Syntax Analysis utilizes line segments; one continuous street segment may be split into several unless it is linear. To go around this issue, we aggregate all Space Syntax Analysis results per Street-Void Unit, by taking a weighted average of all contained line segments' analysis results. The key names for these aggregated variables are presented below (Table 4.3). They start with WAv that stands for “weighted average”.

Table 4.3 : Street network attributes.

Attribute	Explanation
StreetSegment_Length	Total length of segments within STV.
WAv_AngularConnectivity	Weighted average of angular connectivity.
WAv_Connectivity	Weighted average of connectivity.
WAv_Choice400	Weighted average of Choice within 400 m radius.
WAv_Integration400	Weighted average of integration within 400 m radius.
WAv_NodeCount400	Weighted average of node count within 400 m radius.
WAv_TotalDepth400	Weighted average of total depth within 400 m radius.

4.4.3 Streetscape Attribute Analysis

Google Street View is a service that provides panoramic images of streets through an open online platform that allows for the virtual navigation of physical streets with a 360 degree view close to eye-level. The extent of their coverage includes a majority of urban centers in Europe, North and South America, parts of East and South East Asia and Australia. All four neighborhoods studied as cases for this research are covered. The imagery provided is also linked with the Google Maps platform which means they are linked with geo-location information, making it possible to search for these images by geo-location. Through their API this can be automated and the camera angles (heading, pitch, field of view) and sizes of images to be obtained can be adjusted (Google Maps Platform, 2019). Microsoft provides a similar service named Street Side (Microsoft, 2019) integrated with Bing Maps. Yandex also offers street view imagery in a limited number of countries (Yandex, 2019). There are several other similar services including local ones that cover streets within their country of origin. These images are commonly collected through camera installed motor vehicles but for locations inaccessible by car different solutions are also used. Beside cars, Google uses tricycles, snow mobiles, boats or wearable kits to record street view imagery on foot.

Due to the ease of access and the extent of coverage and detail these services provide for street imagery, they have begun to be utilized by several walkability related and other urban research (Glaeser, Duke-Kominers, Luca, & Naik, 2015; Griew et al., 2013; Nguyen et al., 2018; Rundle, Bader, Richards, Neckerman, & Teitler, 2011; Vargo, Stone, & Glanz, 2012). One interesting example that served as a precedent for the methodology used in this thesis is the Place Pulse project through which street view images are classified for various perceptual qualities by a crowd-sourced survey interface that is then used to train the Streetscore algorithm to score new images for these qualities (Naik et al., 2014, 2016).

For the current research, using the Google Street View API and custom Python code, street façade images on both sides of the street were collected every 15 meters with a camera angle that allowed for this frequency to cover the facades in an uninterrupted manner. Next, the images were fed into the online computer vision algorithm Clarifai (Clarifai Inc., 2019) using their API and a custom Python code. Among several image-recognition algorithm models available, most appropriate model to assess street view imagery was found to be the “General Model”. In the images analyzed, the built environment elements and in some instances some conditions detected with a certainty level higher than 90% were utilized. The word tags that were deemed relevant for walkability within these are: tree, landscape, environment, park, door, window, pavement, commercial, business, shopping, chair, bench, furniture, car, vehicle, traffic, calamity, abandoned and demolition. Additionally, instances where people were visible were also recorded and mapped. This information was utilized in evaluating the level of street activity, to be explained in the following section. The explanation of attributes representing these measures are presented in Table 4.4.

While this analysis is valuable in terms of providing opportunity to explore streets at eye level and at remote locations, the reliability of the findings depends on the competence of the image recognizing algorithm. In this study, a generic algorithm was used (Clarifai Inc., 2019), however, a specifically trained one for street views would perform much better. The currently used algorithm is not as accurate as on-site human observers however the level of bias and error will be more consistent across all studied neighborhoods and street segments.

Table 4.4 : Streetscape attributes.

Attribute	Explanation
pavement	Number of street sides where pavements are identifiable
door	Number of street sides where doors are identifiable
window	Number of street sides where windows are identifiable
Permeability	Number of street sides where doors or windows are identifiable
tree	Number of street sides where trees are identifiable
landscape	Number of street sides where landscape is identifiable
environment	Number of street sides where natural greenery is identifiable
park	Number of street sides where parks are identifiable
Attribute	Explanation
Green	Number of street sides where trees, parks, natural greenery or landscape is identifiable
commerce	Number of street sides where commercial amenities are identifiable
shopping	Number of street sides where shopping amenities are identifiable
business	Number of street sides where businesses are identifiable
Commercial	Number of street sides where commerce, shopping amenities or businesses is identifiable
bench	Number of street sides where benches are identifiable
chair	Number of street sides where chairs are identifiable
furniture	Number of street sides where furniture is identifiable
Street_furniture	Number of street sides where chairs, benches or other furniture is identifiable
cars	Number of street sides where cars are identifiable
vehicle	Number of street sides where vehicles are identifiable
traffic	Number of street sides where traffic is identifiable
Motor_transit	Number of street sides where cars, vehicles or traffic is identifiable
calamity	Number of street sides where calamity is identifiable
demolition	Number of street sides where demolition is identifiable
abandoned	Number of street sides where abandoned buildings are identifiable
Negative	Number of street sides where calamity, abandoned buildings or demolition is identifiable
people	Number of street sides where people are identifiable

4.5 Street Activity Analysis

In studies where correlations are sought between walking or other travel behavior and the measured built environment attributes, data is collected on the hypothesized outcome of the built environment characteristics, or the said behavior. Walking behavior data may be in the form of residents' answers to survey questions about how often they choose to walk for utilitarian purposes or for leisure, the duration of their trips, their most recent walking routes or origin and destinations of walking trips. In several studies, pedestrian counts recorded on location and in one case, through Google Street View images (L. Yin et al., 2015) are used as the outcome data to compare against built environment attributes. While the surveys and on-street pedestrian counts pose limitations as they account for the behavior of only a sample of residents within specific time frames and environmental conditions, one of the most accurate walking behavior data utilized in walkability literature is GSM or other GPS based data which enable the tracking and mapping of pedestrian behavior throughout a given period of time (Quercia et al., 2015; The New York Times, 2015). In such studies, a group of participants' pedestrian activity is tracked using their cellular phones or wearable GPS trackers. While such data is more accurate in terms of locations than data collected by any other method, it is difficult to obtain and limited in terms of the set of pedestrians' whose activities are tracked unless extra effort is made to select a random and highly representative sample. Urban dwelling activities of first-time visitors, foreigners or people from different demographics like the elderly and the children will most likely be missed.

One other method that has been employed to track street activity that has become more popular through the availability of data and advance of programming in the urban research fields is the use of geo-tagged data from social networks. Referred to as Location Based Social Network data (LBSN), publicly shared posts with geographical location tags from Flickr, Foursquare, Twitter, Instagram and other social networking platforms are utilized to understand when, where and how people occupy the public space (Cranshaw et al., 2012; Ensari & Kobaş, 2018; Hamstead et al., 2018; Niederer et al., 2015; Quercia et al., 2015; Redi, Aiello, Schifanella, & Quercia, 2018). Besides geo-location information that allows for the mapping and tracking of where activity takes place, the content such as verbal tags provided by users for images; the text that can be analyzed semantically to detect specific responses and preferences; dates and time of day, number of comments, likes and ratings also inform researchers about the behavior of dwellers in the urban environment.

A method utilized in this research was to scrape Google Place locations for each neighborhood and map them to evaluate the frequency of commercial amenities on the streets. Besides being easily accessible through the Google Maps Platform and automatically gathered by custom Python code through the platform's API, this data is considered to be reliable and up to date as a means to assess land use patterns (Martí, Serrano-Estrada, & Nolasco-Cirugeda, 2019), as it is contributed by location owners who want their stores to be easily accessible as well as Google Maps users who frequently update and evaluate location information of amenities they visit. In this research, Google Places data was not used as an outcome of street activity but rather as part of walkability indicator characteristics of Density, Diversity, and Permeability, as will be presented in the next chapter. However, this data was used to scrape Instagram post data as is explained below, since the Instagram platform does not share accurate geo-locations of posts due to security reasons.

The methods used in this study to track street activity were to scrape and map geo-tagged Flickr post data using the Flickr API (Flickr, 2019) as well as Instagram post data automating the Google Search Platform to search for Instagram posts linked with Google Place names of locations within a buffer of the area studied, with custom Python code. Also, the count of instances where people were sighted by the image-recognition algorithm Clarifai (Clarifai Inc., 2019) in the Google Street View images (Google Maps Platform, 2019) were computed which was also utilized to identify streetscape elements. The explanation of attributes representing these measures are presented in Table 4.5. The combination of this data is tested to be used as an outcome of walkability-related built environment attributes, and used as a proxy for walking activity to identify the predictive power of these attributes.

As also acknowledged in literature, the utilization of types of data and data gathering methods discussed in this section are not without limitations (Arribas-Bel, 2014; Martí et al., 2019). The availability and conditions of access are vulnerable to change as these platforms are owned by private commercial companies that can easily change their policies. Also, since the data is crowd-sourced by independent third-party users who are not liable for accuracy of the information they provide, manual or automated methods are needed to filter out these inaccuracies, which in the current study is done through the omission of duplicates and outliers. Additionally, the representativeness of data can always be questioned as the users posting to the social media platforms utilized are expected to own and be familiar with the applications on smart phones which exclude the very young, the elderly, those who do not own smartphones or those people who simply don't use these platforms often or at all. Issues with people counts through street view images using computer vision include the representativeness of samples due to the impossibility to control the time of the year and day when the images were collected. Also, it is common to see the same persons in multiple street view images in the case where their routes coincide with the tracker vehicle collecting the images, which leads to their counting for more than once. Sitting versus walking people are also not distinguished by the image recognizing algorithm used.

Table 4.5 : Street activity and amenity attributes.

Attribute	Explanation	Formula
Flickr_within35	Points where Flickr posts were geo-tagged within 3.5 meters of the STV footprint area.	-
Flickr_pSTVLen	Number of Flickr posts geo-tagged within 3.5 meters of the STV footprint area divided by the length of STV.	Flickr_within35/ STV_Length
Instagram_within35	Instagram post locations liked with Google Places geo-tagged within 3.5 meters of the STV footprint area.	
InstagramPost_pSTVLen	Total number of Instagram posts linked to locations geo-tagged within 3.5 meters of the STV footprint area divided by the length of STV.	Instagram_within35/ STV_Length
GPlaces_within35	Points where Google Place locations are tagged within 3.5 meters of STV.	-
GPlaces_pSTVLen	Number of Google Place locations that are tagged within 3.5 meters of the STV footprint area divided by the length of STV.	GPlaces_within35/ STV_Length
people	Average number of street sides where people were sighted for each street segment.	

Nevertheless, as the data utilized is subject to these issues for all cases studied, the comparison of people counts across different cases as done in this study presents a consistency. Furthermore, the practicality of these methods compared to on-site audits that are not without their own limitations, renders it a promising means to access pedestrian activity information in future research, together with the advance in the technology, the availability and reliability of open data.

4.6 Statistical Analysis of Case Study Results

The analysis workflow laid out in detail in the previous section is applied to four neighborhoods to derive quantitative inferences. The results of the case studies are first explored using descriptive analysis, looking at boxplots where attribute values are summarized and compared for each neighborhood. A detailed account of the selection of cases and the descriptive analysis of attribute values are presented in Chapter 5.

Following this analysis, the attributes of Flickr post frequencies (Flickr_pSTVLen), Instagram post location frequencies (InstagramPost_pSTVLen) and the number of street sides (NSS) where people were detected using computer vision software on Google Street View images (people) were tested as outcome variables by developing a predictive regression model. A set of attributes from those defined above were selected based on how theoretically significant and arithmetically representative they were at the same time eliminating those expected to have covariance. For example, STV_Width and STV_Height were each considered important separately so STV_HeightTWidth variable was eliminated. Also, some attributes that did not consistently align with expected levels of differences between neighborhoods were eliminated. Examples to these are the diversity attributes measured with coefficient of variations (Cov) among values for street chunks (Convex-Voids) within street spaces (STVs). The predictive model trained using part of the samples and tested on the remaining is utilized first to assess whether the social media and street view-based outcome variables can quantitatively represent walkability, in other words, used as a proxy to measure the levels of walkability. This assessment of the predictive model relies on theory derived from the literature review and knowledge gained from the descriptive analysis of attributes in the preceding chapter. Secondly, it is used to assess the significance of each attribute in determining the popularity of each street. Next, a set of attribute values for all samples are fed into a K-means clustering algorithm to group streets into clusters based on their similarity of values. Among 5, 6, 7 and 8 clusters tested, 6 was found as the most meaningful number of clusters looking at maps of grouped samples and their known characteristics. These clusters are also compared to street typologies defined in literature and their attribute values are subjected to descriptive analysis, results of which are summarized in boxplots. This part of the study is presented in Chapter 6.

The observations based on the analysis in Chapter 6 result in the identification of some distinguishing attributes on which we base a second classification of the studied samples as well as selecting a final, reduced set of attributes. Looking at the summarized values of these classes of our street space samples, we identify threshold values for attributes that delineate walkable and non-walkable streets. Based on these, we present a step by step guideline to assess the walkability of neighborhood streets using our proposed workflow in Chapter 7.

5. CASE STUDIES

This chapter presents the analysis of the results obtained from the evaluation of the four neighborhoods using the semi-automated data collection and evaluation techniques presented in the previous chapter. Preceding the initial observations, some historical background is provided with some observed and quantitative comparison of the walkability related characteristics of the selected cases.

5.1 Selection of Cases: History and an Initial Comparison

Four mainly residential areas in different neighborhoods were selected for case study. Two were from Istanbul's Kadıköy district: Caferağa and Hasanpaşa and two were from Lisbon: Chiado from the Misericordia district and an area from the district of Ajuda.

Even though Caferağa and Hasanpaşa neighborhoods are both within the boundaries of Kadıköy district and the areas of study are within twenty minutes walking distance, their physical and socio-cultural make-up has shown very different historic progressions. While both neighborhoods' street network structures have remained similar to their early 20th century versions apparent in maps from 1906 (Goad) and 1922 (Societe Anonyme Ottomane d'Etudes et d'Entreprises Urbaines) for Caferağa and a 1930 (Pervititch) map including Hasanpaşa's south west area; the building stock, plot divisions and bulks have shown significant transformation in both areas due to rapid densification following the modernization of the late Ottoman Empire, than the Turkish Republic and finally, the urban transformation of Istanbul after the 1999 earthquake.

The larger Kadıköy area is known to have been settled by the Ottoman Turks around 1350s. The district developed mainly after the late 19th century following the building of the Haydarpaşa-İzmit railroad and the start of the ferry service connecting the neighborhood to the European side (Akbulut, 1994). According to Sezginalp (2017), Moda neighborhood (that constitutes the majority of the Caferağa study area at its south) was preferred by the wealthy, non-muslim minorities of the Ottoman population where they built “köşk”s and “konak”s that were mostly three story mansions with large gardens housing extended families and throughout the modernization during the early republican period, the neighborhood continued to be preferred by the elite where they commissioned architects and built modern houses. Around the 1960s more middle and upper-middle class families began to move into this neighborhood, after which it began to densify with concrete apartment buildings of 4-5 stories with footprints leaving smaller setbacks and taking up most of the lot areas previously used as gardens around detached houses (Sezginalp, 2017). Nevertheless, the neighborhood still accommodates several historic monuments, old mansions and apartment buildings retaining some of its character. Still housing a higher-income population compared to the majority of the other neighborhoods of Kadıköy including Hasanpaşa, it has also become popular with young professionals and families that live in or visit the several cafes and restaurants in the neighborhood during the weekends. The historic bazaar “Kadıköy Çarsı” constitutes the northern part of the study area which formed by the aggregation of shops and restaurants to the area following the construction of several mosques, churches, bath houses and other monuments during the Ottoman rule. Compared to the southern quarter, the bazaar area has narrower streets and lower buildings with fewer residences and a density of restaurants, cafes, food vendors and stores. The street network of this area dates back to the grid plan with 8 to 10 m wide streets and squares created by clipping the block corners made following the fire of 1856 (referred to as 1860 too) that destroyed 250 buildings in the neighborhood (Akbulut, 1994).

While Hasanpaşa had not been a dense residential neighborhood until the late 19th century, with the construction of a mosque and a gas factory providing electricity and water to the neighborhood around then, Turkish families began to move into the neighborhood (Gökçen, 1994). According to Mazbaşı Berktay (2012), having been home to middle and low-income families until the 1980s, with the development of the neighboring Selamiçeşme as a commercial center pressuring the neighborhood, Hasanpaşa transformed where traditional building stock of timber and masonry houses of 2-3 stories were rapidly replaced by larger, concrete and up to 5 story buildings with commercial uses at the ground floor. This transformation has been very different from that of Caferağa. Never having been a wealthy neighborhood in the first place, Hasanpaşa was pressurized into hap-hazard change and loss of character due to the slum population of adjacent Fikirtepe neighborhood; most of the traditional building stock was replaced if not badly renovated, roads were widened and the greenery was destroyed by new construction (Mazbasi Berktay, 2012). The large lot at the center of the study area belonging to the old Gas Factory that is designated to be converted into an energy museum through renovation is surrounded by construction barriers of approximately 500 meters, without any sidewalks.

Chiado, situated in the center of Lisbon, is one of the most popular neighborhoods in the city as a tourist attraction. Being within the bounds of the city walls constructed at the time of King Ferdinand I in the 1300s (only a small eastern part of the study area would be within the walls), the neighborhood grew rapidly with several public buildings being constructed, some of which still exist today (Morais, 2015). Following the 1755 earthquake, several buildings were repaired and reconstructed with Marquis Pombal’s grand renewal project. Maps from around this time show an almost identical street network to the current one (Carvalho, n.d.; Mentelle, 1782). The following centuries witnessed the opening of several shops in the area and conversion of residential buildings to commercial stores as it became the popular shopping neighborhood that it is today. One of the reasons for the famous 1988 fire that destroyed several buildings in the neighborhood- they remain outside the boundaries of the study area- is said to be this commercialization, as lack of residential units in the area caused the streets to be deserted during the night raising the risk for undetected fire hazards (Neves, Valente, & Branco, 1995). Even though there is abundant activity and nightlife in the area today, it is a mainly commercial area with hotels, guest houses and apartment rentals catering to tourists due to their high prices.

Ajuda neighborhood was mostly shaped around the church and hermitage of Nossa Senhora da Ajuda that was established in the 1500s as a pilgrimage point and attracted a settlement around it. After the earthquake of 1755, the king of Portugal decided to build his palace in the area considering it safe due to being settled on rock and protected from tsunamis due to high elevation, which resulted in rapid increase in population with the palace servants and craftsman moving to the area (Junta de Freguesia da Ajuda, 2019). The main street Calçada da Ajuda that goes through the study area in the north-south direction, is known to have been important after this period as it led to the Royal Barracks temporarily built as a summer house for the royal family and eventually, the National Palace of Ajuda (Guerra, 2018). This street still preserves its significance as one of the main streets of the neighborhood and its sidewalks were renovated recently. Tracing the cartographic maps of Lisbon in history, the majority of the streets of the study area in Ajuda seem to have started being built in the mid-19th century with the main streets along with the current Police Head Quarters building visible in a 1856-58 map (Folque, 1871). The building stock consists of two to four story residential buildings and on the eastern part of the study area are larger residential blocks that go up to 5 stories.

Among the four neighborhoods, Caferağa and Chiado, both selected as more walkable compared to Hasanpaşa and Ajuda are recently going through gentrification with the opening of new commercial amenities to serve the influx of local and international tourists visiting the areas and the real estate prices rapidly climbing up. While Ajuda is known to be slightly influenced by the fast-growing tourism industry in Lisbon with some locals renting out their apartments to visitors, its population is aging and getting smaller in size and the residents complain about the decline (Cristino, 2018). Hasanpaşa, on the other hand lacks the amenities, points of attractions and character that could attract any sort of tourism yet its population is growing as a result of the densification of neighboring commercial and residential zones.

It is undeniable that the diverse historical backgrounds of the four neighborhoods to be studied have a considerable impact on their current physical, socio-cultural and economic makeup and thus how walkable they are today. In principle, the earlier a neighborhood was built and the less it has changed in terms morphology, the more likely that it will have narrower streets that are intended less for cars and more for pedestrians, and that the scale of building facades and other streetscape elements will be closer to human scale. Historical monuments, landmarks and traditional housing play an important role in rendering the streets more attractive and interesting for the pedestrians (Ewing & Handy, 2009; Lynch, 1960) and so their conservation becomes of great consequence. On the other hand, hap-hazard renovation projects, widening of the streets to accommodate more traffic, replacement of buildings with larger and taller structures have a negative impact on how comfortable, safe and attractive a neighborhood feels. Abandoned buildings or lots, sites closed off by construction walls, demolished buildings and badly maintained streets lower the level of walkability both by physically impairing conditions for walking and weakening the feeling of safety and security. Additionally, mixed rather than single-use zones are known to prevent negative impacts on livability such as lack of safety and security as well as noise, congestion and use of the streets being concentrated to certain times rather than maintaining a lively street life throughout the day (Balsas, 2007).

The measures presented in this thesis are proposed to account for the outcomes of some of these issues which are quantifiable, however, they were also taken into consideration in the initial selection of the four neighborhoods to be studied as cases.

Besides the historical background, the choice of the areas selected within these neighborhoods also require to be supported by quantifiable evidence, in order for the quantitative walkability measures that are proposed to be coherently comparable. The criteria below describe the reasons behind this choice supported by initial quantitative comparisons and maps (Tables 5.1- 5.3 and Figures B.1-B.8).

- The study areas are roughly similar in size, road density (total length of roads/study area, in sqm) and built area footprints.
- The boundaries encompass a coherent set of streets and do not cut through an axis or open space commonly perceived and used as part or continuation of an included space, unless interrupted by administrative boundaries.
- One study area from each city is assumed as more walkable (Caferağa and Chiado) while one area from each as less walkable (Hasanpaşa and Ajuda). These assumptions were based on personal experience and observation, but are supported by the following commonly accepted indicators of walkability:
    - Density based on built area (Table 5.2).
    - Diversity based on google places frequency in the four areas (Table 5.3, Figures B.7-B.8).
    - Activity on the streets measured by number of times people were identified on Google Street View image captures and social media activity based on geo-located Flickr post counts (Table 5.3).

Additionally, since the purpose of the case studies is to understand how built environment characteristics influence walkability in a more granular level, the variation of these characteristics among the streets within each neighborhood was also taken into consideration.

Table 5.1 : Neighborhood demographics.

	Neighborhood Area	Neighborhood Population	Population Density	Study Area
Caferağa	1,240,000	23,980	0.0193	297,000
Hasanpaşa	798,000	15,580	0.0195	329,000
Chiado	1,118,000	13,050	0.0117	385,000
Ajuda	2,885,000	15,620	0.005	417,000

Table 5.2 : Neighborhood density statistics.

	Total Building Area(m2)	Building Area Density	Total Floor Area (m2)	Floor Area Density	Total Street Length (m)	Avg Street Segment Length (m)	Road Density (m/sqm)
Caferağa	158,600	0.535	778,550	2.63	7,200	59	0.0243
Hasanpaşa	122,650	0.373	476,000	1.45	7.22	70.7	0.022
Chiado	196,700	0.511	923,450	2.4	9.57	48.8	0.0248
Ajuda	147,200	0.353	501,000	1.20	10.67	64.6	0.026

- The streets within each area showed enough variation compared to each other in terms of activity based on Flickr (Table 5.3) and number of sides where people were sighted as well as the frequency of Google Maps places (Figures B.7 – B.8).

Table 5.3 : Neighborhood activity statistics.

	Total Flickr Posts (06.09.06 -25.02.19)	Avg Number of Flickr Posts per m of Street Length	Total Number of Google Places	Avg Number of Google Places per m of Street Length	Number of Types of Google Places	Total NSS were people were sighted (per 15m for each segment)	ANSS were people were sighted per m of Street Length
Caferağa	477	0.066	539	0.075	22	267	0.037
Hasanpaşa	28	0.004	277	0.038	21	102	0.014
Chiado	275	0.029	608	0.064	22	120	0.013
Ajuda	59	0.006	83	0.008	17	38	0.004

- Upon initial observation, the streets within each area showed enough variation compared to each other in terms of morphological and streetscape characteristics. This observation was not confirmed until the results of this study were obtained and analyzed. Only the variation in street lengths were measured and compared initially (Figures B.13 - B.14).

A closer look at the numbers reveals the following and support our choice of areas for case study in terms of expected levels of walkability:

- The built area densities of study areas initially considered walkable (Caferağa and Chiado) are about 44% higher and the floor area densities are between 80% to 100% higher than study areas considered not walkable (Hasanpaşa and Ajuda).
- Streets are shorter in Caferağa and Chiado, making blocks smaller and street nodes more frequent.
- While the number of types of Google Place locations are similar in all areas (17 to 22), the densities per street length are significantly higher for Caferağa and Chiado (0.075 and 0.064/m) and extremely low for Ajuda (0.008/m).

5.2 Street Activity Analysis Results

Based on all this information, we expect Caferağa and Chiado which are considered more walkable and measured to have indicators aligned with our assumptions to show more street activity than Hasanpaşa and Ajuda which are considered less walkable. To confirm, we look at social media activity and Google Street View (GSV) images analyzed for sightings of people:

- Density of Flickr posts/street length within the areas of study are significantly higher in Caferağa (0.066) and then in Chiado (0.029), 94% and 80% lower in Hasanpaşa and Ajuda.
- Number of street sides (NSS) where people were sighted in GSV images are lower in Lisbon areas compared to Istanbul areas. This may have to do with the difference in overall population density between two cities and the times of day the GSV imagery was collected. Nevertheless, within cities, the walkable areas of Caferağa

and Chiado show more than double the number of instances where people were seen compared to Hasanpaşa and Ajuda.

Following these initial analyses supporting our choice to study these four neighborhood areas for walkability, the purpose of the proceeding analysis is to:

- Test our proposed analysis methods in quantitatively measuring the morphological and streetscape qualities of the four neighborhoods' streets and see if the results, based on these characteristics' expected impact established in literature align with and support the assumptions regarding the relative walkability levels among the four neighborhoods.
- Investigate the explanatory power of the morphological and streetscape characteristics for the variation in measured street activity within the streets in each neighborhood and within all the studied streets across the four neighborhoods.

The intended outputs of the following study are:

- The definition of a set of morphological and streetscape characteristics that can be measured using remotely accessible data which can effectively account for variation in walkability as well as a semi-automated workflow for their operationalization.
- A set of quantitative evidence-based recommendations for urban design decisions based on findings.

In addition to the above-mentioned initial analysis to support the choice of our study areas, Space Syntax analysis of the street segments within the study areas were carried out for Choice, Integration, Node Count and Total Depth with 800 and 1200m radii. These results are not as straight-forward to interpret as the morphological data presented above therefore are not presented as evidence that support our choice of study areas. One obvious result legible in the maps is that Chiado values for all measures are significantly higher. All measures expected to be higher for the walkable neighborhoods of Chiado *and* Caferağa, the reason behind the lower values for Caferağa is predicted to be the water bounding the western side of the study area therefore the street network being interrupted on this side. The 400m radii analysis results of the same indicators are presented later in the chapter as aggregated per unit area of study.

The maps referred to in this chapter and the Appendices use the complete result data sets of all indicators whereas the box plots show the results with outliers omitted for each study area. The outliers are computed with the following formula (Formula 5.1) for each neighborhood.

$$> Q3+1.5*IQR$$

$$< Q1+1.5*IQR$$

IQR: inter-quartile range

Q1: first quartile, Q3: third quartile

(5.1)

5.3 Morphological Analysis Results

Maps in the Appendices present:

- The morphological attributes and characteristics of streets measured using Convex and Solid-Void indicators aggregated per Street-Void (STV) for each study area (Appendix-C).
- The building statistics such as footprint and floor areas aggregated per STV (Appendix-D).
- The Space Syntax values measured in a radius of 400m aggregated per STV weighted based on street length (Appendix-E).

Morphological properties, attributes and their expected relationship with walkability based on literature as well as an initial look at the maps and box-plots are presented below. Note that boxplots represent the five number summaries of each variable's value set for the samples analyzed. These consist of the maximum, median and minimum values of the value ranges as well as the 25^{th} (quartile 1 or Q1) and 75^{th} (quartile 3 or Q3) percentile values of the dataset. The box's bottom limit represents Q1, band near the middle represents the median and the upper limit represents Q3. The whiskers in this study represent Q1-1.5*interquartile range (IQR) at the bottom and Q3+1.5IQR at the top where IQR is the difference between Q3 and Q1, or the range represented by the box. Also, where outliers are omitted, the IQR's are recalculated within the remaining data set.

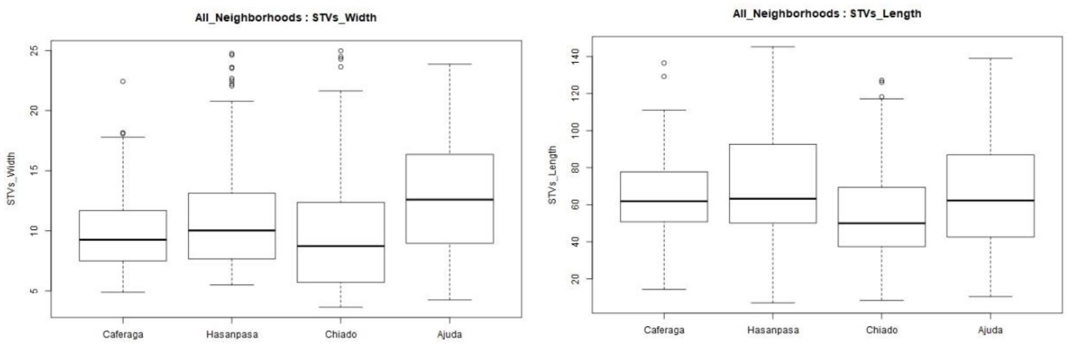
STV Width, Length and Area: Streets are better connected when short and have higher enclosure when narrow, therefore STV Areas are expected to be smaller in areas with higher walkability. Smaller width and area values also mean more variation and closeness to human scale of street spaces; thus, they have higher potential to be more interesting, attractive and human scaled- and so walkable- streets. Shorter STV lengths indicate shorter blocks, which is strongly supported in literature to enhance walkability. Street widths are average width values per STV.

Observations: While all studied neighborhood areas seem to show a variety of width and street space areas, Hasanpaşa and Ajuda have long and large uninterrupted streets with large STV areas, with Hasanpaşa having wider and longer streets compared to Caferağa, and Ajuda compared to Chiado (Figures 5.1-5.2). This is expected as Caferağa and Chiado are assumed more walkable than Hasanpaşa and Ajuda. However, we also see in the maps that Chiado has the largest widths within its STVs (maps show these outlier values whereas boxplots do not) even though it is selected as one of the more walkable neighborhoods. These open spaces are in fact squares with larger widths and overall sizes that are actually very active spaces which contribute to the high walkability level of this neighborhood. Such open spaces should be regarded differently than streets when considering walkability as they contribute positively to walkability with high levels of street activity. As is repeated in the several observations regarding morphological and streetscape properties and attributes to follow, such findings highlight the complexity of urban phenomena. Even though quantitative analyses are highly beneficial in helping support urban design decisions through evidence, they are rarely all-encompassing or easy to generalize. Various categorizations pertaining to different cases may help in such situations and assessment results should always be interpreted with additional physical, use-related, social, cultural and economic urban issues. In the case of STV_Width information, streets and squares can initially be categorized separately based on their areas and shapes then compared within their categories for this value. In the current analysis, the Chiado squares are excluded in the box plots due to being outliers so the results confirm what is expected.

STV Height: STV heights are calculated based on the average height of buildings as well as the proportions of neighboring STVs (see formula 4.1) to emphasize the effect of transition from wider or narrower open spaces. Buildings that are more than 3.5m away from the street boundaries do not affect this measure, whereas their fences or other bounding walls do, if they are within 3.5 meters. Based on the assumption in walkability literature that better enclosure promotes more walkable open spaces, this measure is expected to be higher in Caferağa and Chiado.

Observations: As expected and can be seen in the maps (Figures C.7-C.8) and boxplot (Figure 5.3), Caferağa has higher STVs then Hasanpaşa and Chiado, compared to Ajuda. Chiado in fact has the highest STVs in the data set. This points to higher densities, as well as contributing to the higher enclosure values and therefore the enhancement of the feeling of being in an outdoor room, that is accepted to have a positive effect on walkability.

STV Height/Width: This measure is expected to be higher in Caferağa and Chiado as it indicates enclosure and better walkability.



(a) **(b)**

Figure 5.1 : (a) STV Widths. (b) STV Lengths.

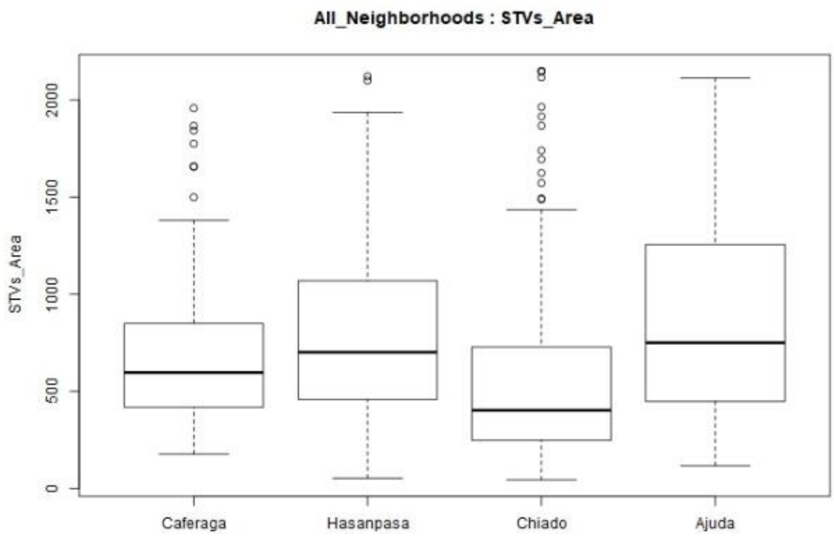


Figure 5.2 : STV Areas.

Observations: Aligned with the expectation that the more walkable neighborhoods will have better enclosure therefore higher height/width ratios, Chiado shows the highest visible values and Caferağa values are higher than Hasanpaşa (Figures C.9-C.10, Figure 5.4).

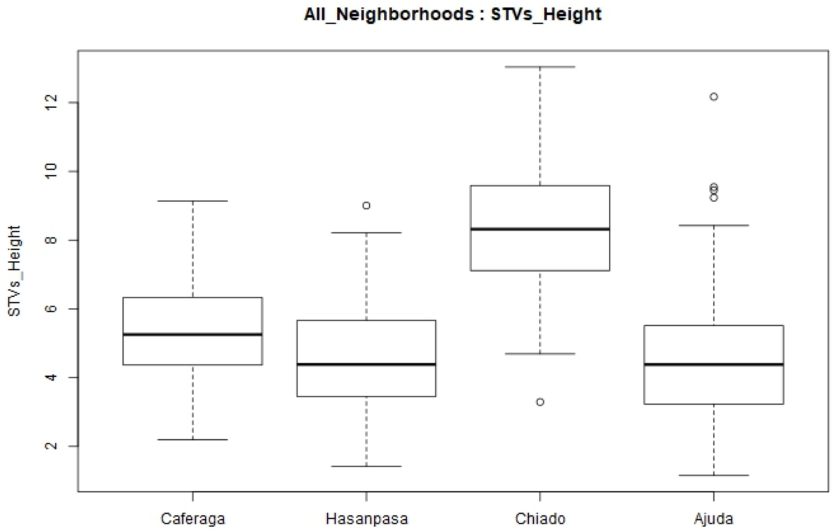


Figure 5.3 : STV Heights.

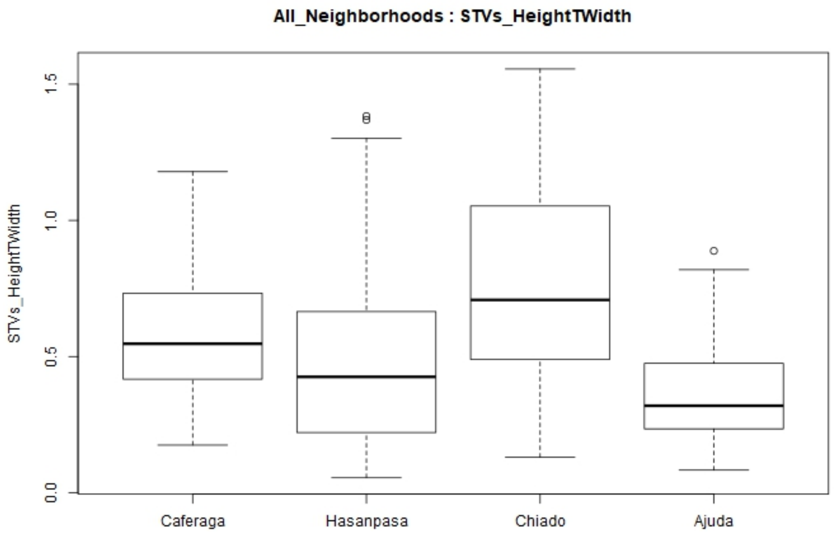


Figure 5.4 : STV Height to width ratios.

STV Enclosure, measured in 2d based on the percentage of street edges taken up by buildings or other surrounding limits such as walls, fences or hedges give a basic idea about whether the street wall is continuous, and if buildings have no setbacks whether they are attached, detached or have large gardens or empty spaces between each other. Higher enclosure is expected to increase walkability but this measure should be considered together with 3d information such as building heights as well as the widths of streets and other formal qualities of street spaces such as compactness and squareness.

Observations: Both maps (Figures C.11-C.12) and the boxplot (Figure 5.5) show no correlation with expected value ranges based on walkability, however other indicators of enclosure do, such as STV Height/Width ratio and CS Average Skyview factor. This is most likely due to this indicator not representing 3d information whereas the walking experience being highly sensitive to 3d built environment characteristics.

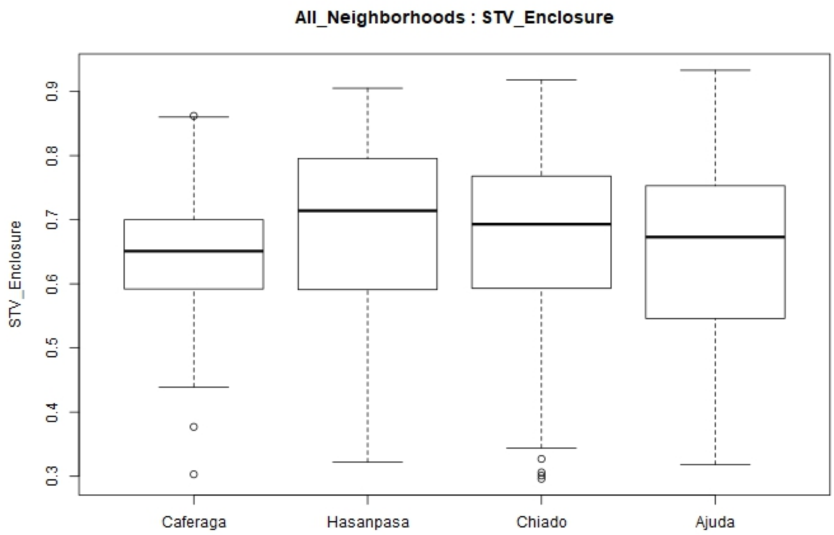


Figure 5.5 : STV Enclosures.

Sky View Factor: The lower this value, the higher enclosure will be. Also, it indicates lower building heights, lower density and lower potential of activity on a street.

Observations: We expect and also see lower values for this measure in Caferağa and Chiado. The fact that the sky view values which are calculated through the 3d model align much better with assumed walkability levels of neighborhoods (Figure 5.6) as opposed to the enclosure values which are calculated based on 2d measures of façade occupied perimeter percentages (Figure 5.5) imply that 3d measures should be preferred over 2d measures in assessing the feeling of enclosure/openness in the built environment. This measure can be interesting to explore together with change in elevation as higher values may indicate opportunity for attractive sceneries that may contribute to walkability positively.

STV_PerimTArea: While the perimeters of STVs also indicate the sizes therefore the lengths and widths of STVs, this indicator which is a ratio between the perimeter and area of an STV is concerned with the level of articulation or how faceted the boundaries of an STV are. The higher this value, the more intricately divided a façade will be, which we assume to point to more opportunities for diversity of uses. Higher number of divisions per façade could mean there are several different buildings or varying types of limits throughout a street length, or a single building or boundary may have different facets which along with different uses may also point to varying elements, surfaces and material treatments. Contributing to both diversity and visual complexity, this indicator is expected to have higher values in more walkable neighborhoods.

Observations: Even though the maps (Figures C.15-C.16) do not show obvious expected results due to some outliers in Hasanpaşa, the boxplot (Figure 5.7) shows that ranges and medians somewhat align with expectations: Caferağa and Chiado show higher levels of articulation. Since the differences are slight, this indicator should be considered together with other indicators of diversity and complexity. It should also be noted that this indicator does not differentiate between buildings and other limits or account for 3d qualities.

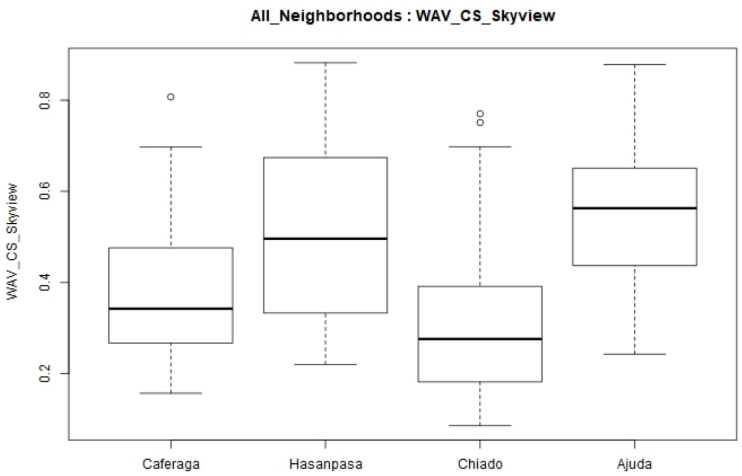


Figure 5.6 : WAv of Skyview values per STV.

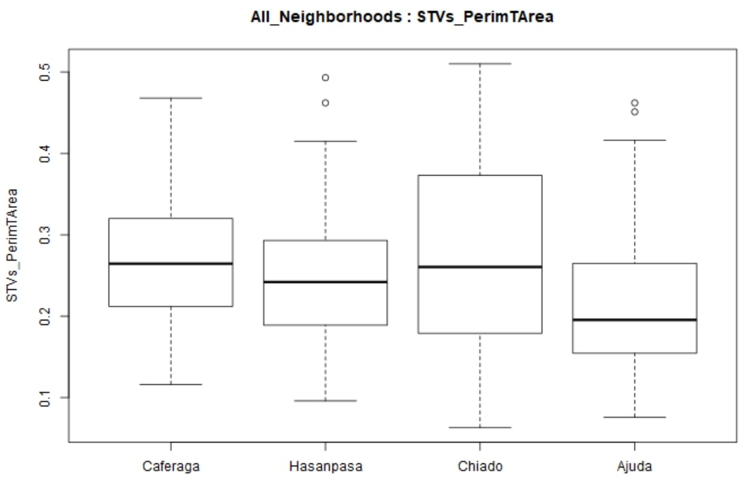


Figure 5.7 : STV Perimeter to area ratios.

Flow Length per STV Area: Flows are auto-generated entities by the Convex and Solid-Void method that are similar to street segments. However, they are different in that the street segments used in this research is based on the street network geometry obtained from municipalities therefore exclude stairways and other passages whereas the flows are based on the continuous centerlines of street spaces and therefore take into account all possible passageways. This means flows also take into account the articulations in the STV shape and represent all possible connections as opposed to the shortest segments that go through a street space which the actual street network segments usually correspond to. Thus, this indicator is a measure of both morphological articulation and diversity as well as connectivity.

Observations: Caferağa and Chiado show higher range values of this indicator compared to Hasanpaşa and Ajuda as expected (Figure 5.8), similarly with other connectivity and diversity measures but the median values are higher in Istanbul than in Lisbon. This measure should be considered together with other complexity and connectivity indicators.

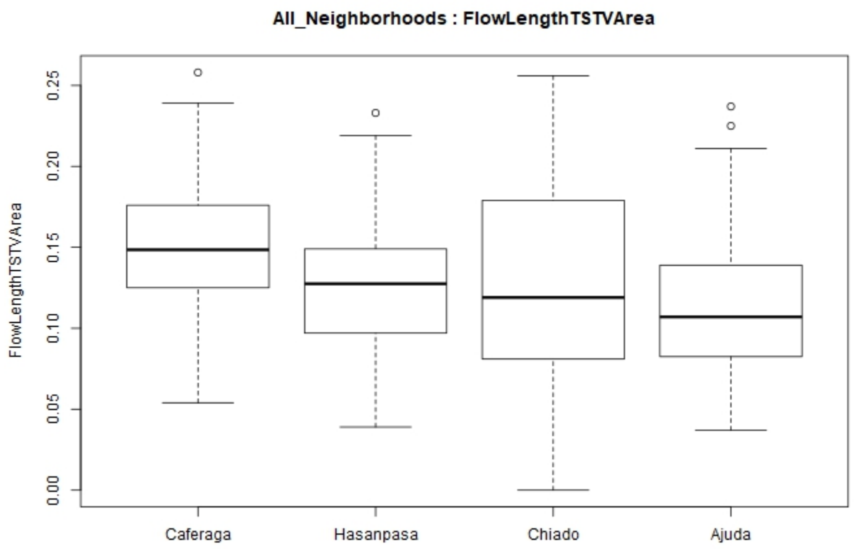
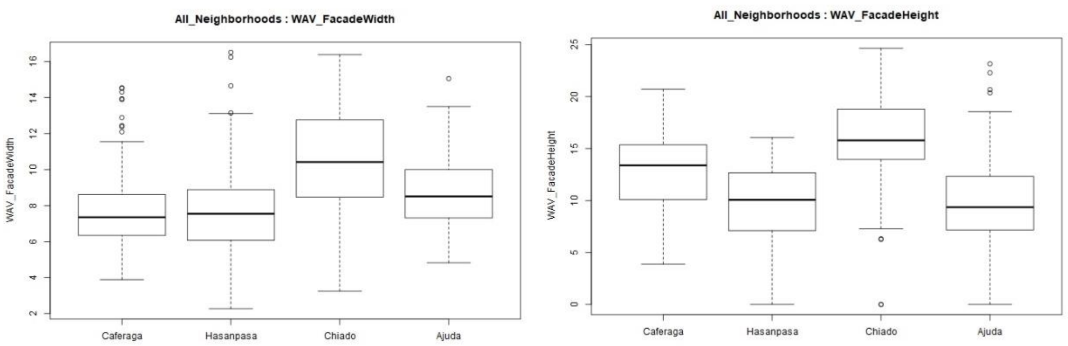


Figure 5.8 : STV Total flow length to area ratios.

Weighted Average of Façade Widths, Heights and Areas: These indicators measure the weighted average of all bounding street facades' widths, heights and areas. While the height values also point to higher enclosures and where the limits are buildings, higher densities in terms of built area, the widths of facades mean less potential for articulation and diversity. Combined together, the façade areas also indicate larger, less divided bounding limits that contribute negatively to human scale. Thus, while the widths are expected to be lower in highly walkable neighborhoods, the increase in height is expected to contribute positively to walkability.

Observations: Height values align with expectations as they are greater in Caferağa and Chiado, contributing to walkability by enhancing enclosure and increasing likeliness of higher densities in terms of built area. On the other hand, width values do not show obvious correlations at an initial look (Figure 5.9). Façade areas, along with the heights are greater in Caferağa and Chiado therefore we may infer that heights should be considered a more reliable indicator than façade widths and areas for walkability (Figure 5.10).



(a) **(b)**

Figure 5.9 : (a) WAv of façade widths. (b) WAv of façade heights.

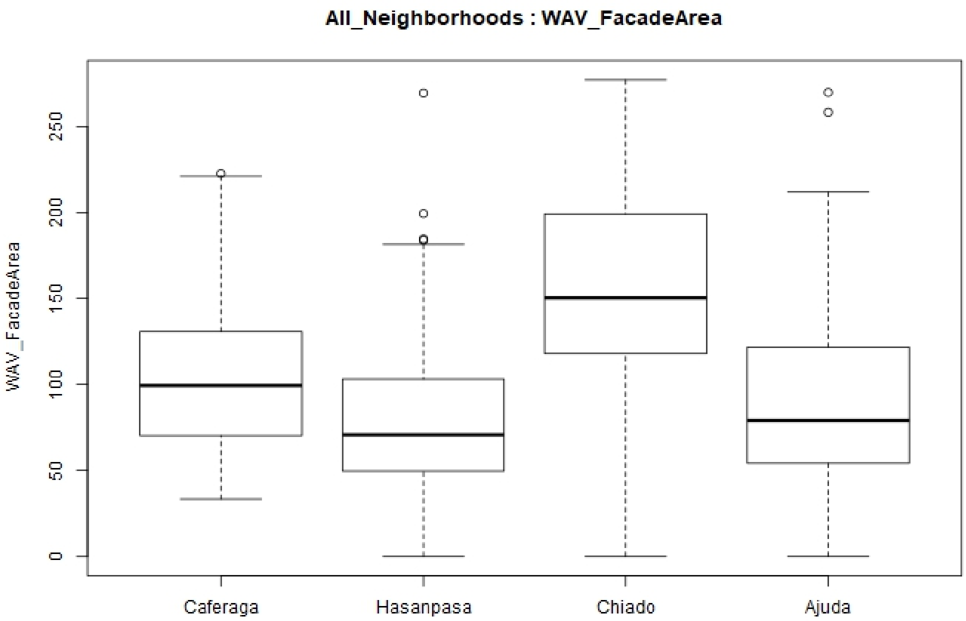


Figure 5.10 : WAv of façade areas per STV.

Façade Height to Width Ratio: Calculated through taking the weighted average of all facades' height to width ratios surrounding an STV, this measure is expected to positively correlate with walkability as taller facades provide higher levels of enclosure and may indicate higher densities if they belong to buildings and narrower facades offer potential for more diverse uses and visual complexity.

Observations: No obvious correlations are observed in the data set (Figure 5.11). Chiado being one of the neighborhoods considered to have higher walkability levels, has larger building facades in terms of both height and width. Feeling of enclosure is enhanced by the heights of these buildings but widths do not seem to contribute negatively. This indicator should be studied further.

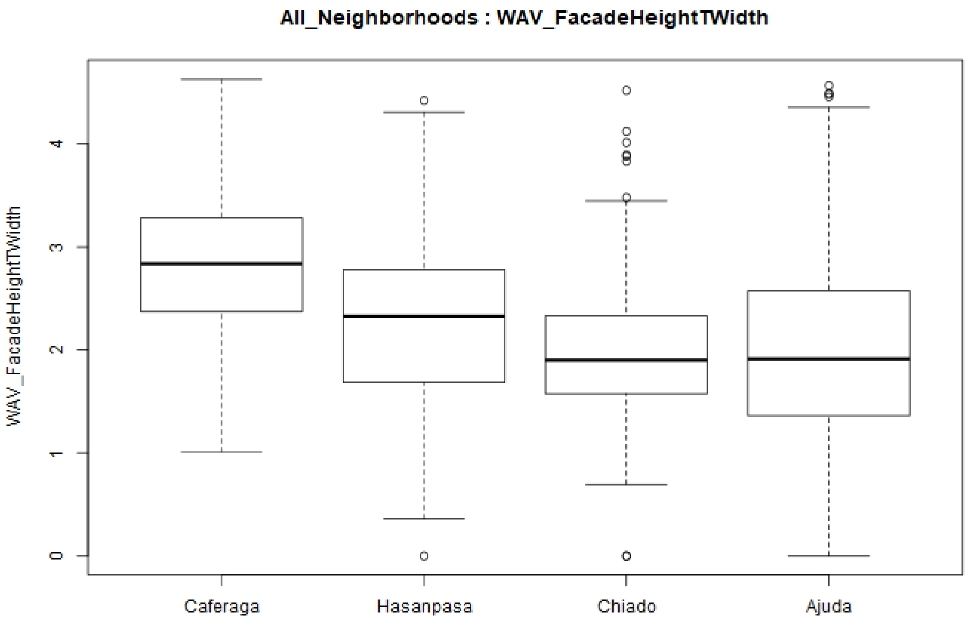


Figure 5.11 : WAv of façade height to width ratios per STV.

Building related properties and attributes:

Number of Buildings per STV Length: Dependent on both the façade widths and how much of the street side is taken up by buildings, this attribute concerns the complexity characteristic. It is also commonly referred to and utilized in quantifying walkability related built environment qualities in literature. It is expected to positively correlate with walkability.

Observations: Expectedly, Caferağa and Chiado have higher values than Hasanpaşa and Ajuda, even though the differences are not very significant (Figure 5.12).

BArea and **FArea per STV Length** and **per STV Area**: are calculated by dividing the total building footprint areas and total floor areas of all buildings surrounding an

STV by the STV length or area and indicate density. They simply look at the built square meter density calculated based on the 3d geometry of buildings.

Observations: As expected, these values are higher in Caferağa and Chiado (Figure 5.13). Variations in streets within each neighborhood should be studied together with street activity and other indicators.

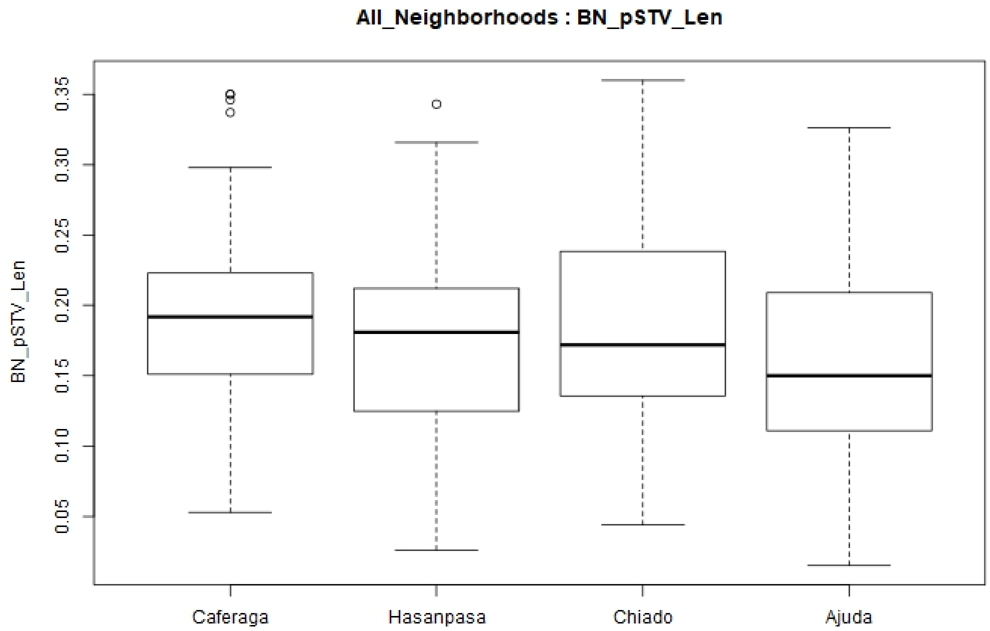
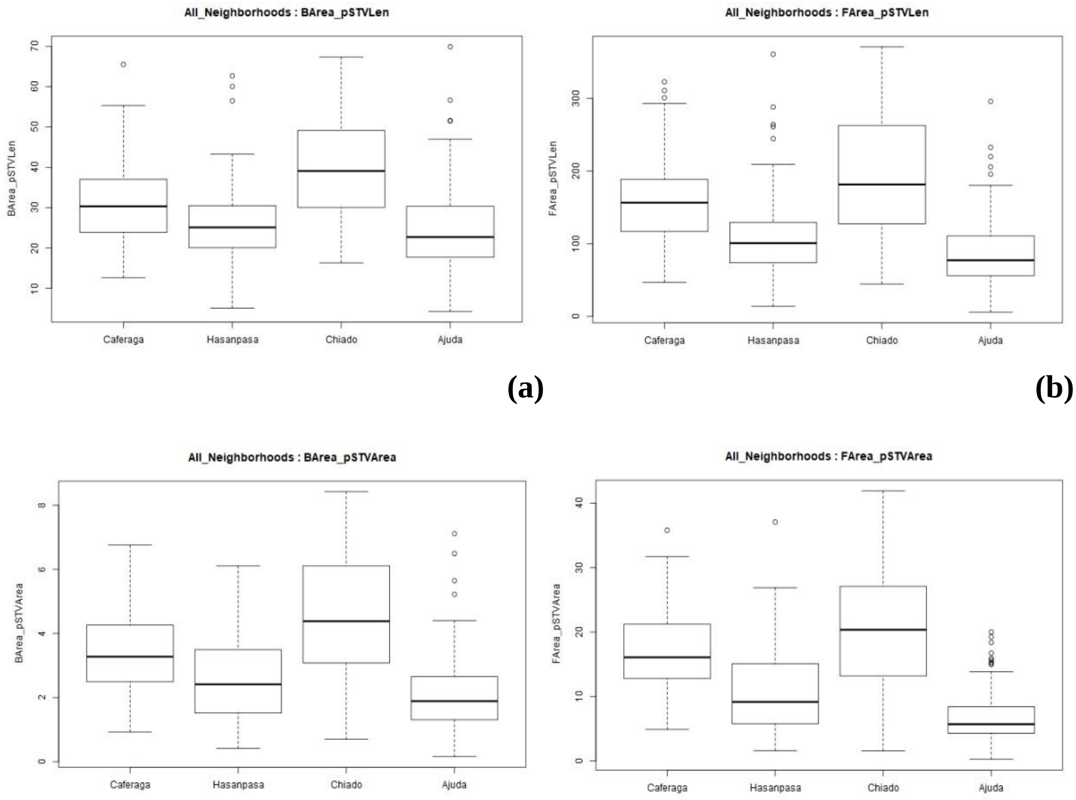


Figure 5.12 : Number of buildings per STV length.

Average Building and Floor Areas, Average Floors: These values are calculated by dividing total building areas, floor areas and number of floors with the number of buildings surrounding an STV and are indicators of both diversity and also scale. They may contribute positively to walkability by indicating higher densities but the greater these values are, the larger building footprints and heights are indicated. While higher buildings are known to indicate density and better enclosure, large footprint areas are interpreted in this research as less articulation and less potential for diversity.

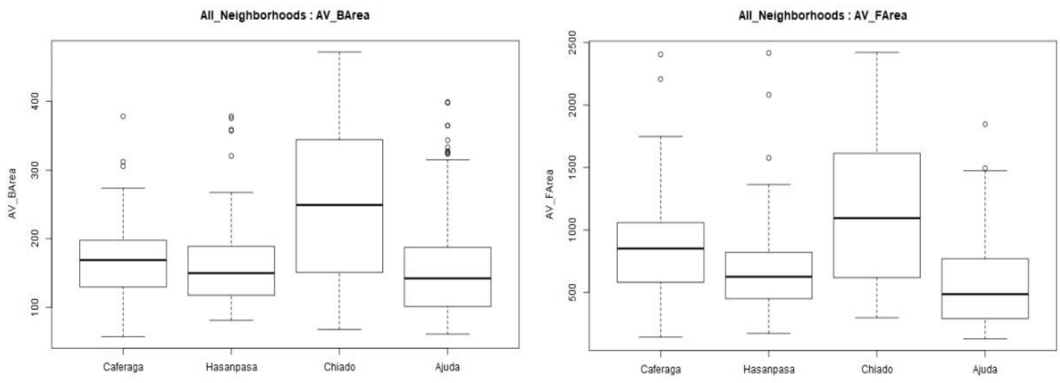
Observations: While the average number of floors seem to align best with the assumed walkability levels, the average floor areas follow with similarly higher values in Caferağa and Chiado as expected (Figures 5.14-5.15). However, Building Areas do not show obvious correlations. This may confirm the expectation that while building heights contribute positively to walkability due to increasing density and enclosure, footprint areas of buildings do not, as larger footprints indicate less articulation and again, less potential for diversity.



(a) (b)

(c) (d)

Figure 5.13 : (a) Building areas per STV length. (b) Floor areas per STV length. (c) Building areas per STV area. (d) Floor areas per STV area.



(a) (b)

Figure 5.14 : (a) Average building areas. (b) Average floor areas.

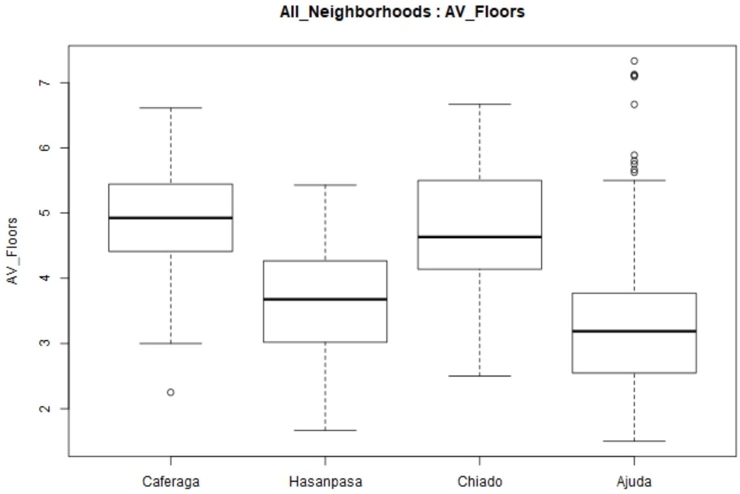


Figure 5.15 : Average number of floors.

Street network measures:

Weighted average values (WAv) of Connectivity, Angular Connectivity, Choice, Integration, Node Count and **Total Depth** are Space Syntax measures of line segments, aggregated per STV. The aggregation is done by taking the average values of these measured indicators for each Street Void and weighing them based on their lengths. Choice, Integration, Node Count and Total Depth values are measured within a 400m radius from the center of each area of study, therefore, they take into account a larger region of street network than is within the study boundaries.

While these values were initially computed for larger radii of 800m and 1200m as well, within the studied scale, values based on the 400m radii were deemed sufficient for representing street network qualities.

Observations: Choice, Node Count, Integration and Total Depth are expectedly high in Chiado. These values are are also higher in Caferağa compared to Hasanpaşa. Caferağa, however is bounded by water on the west, therefore its streets show lower values for all these measures compared to the streets of Chiado (Figure 5.16). Based on the values measured within the studied samples, Connectivity and Angular Connectivity seem to be less parallel with the assumed walkability levels then the Space Syntax indicators of Choice, Node Count, Integration and Total Depth (Figure 5.17).

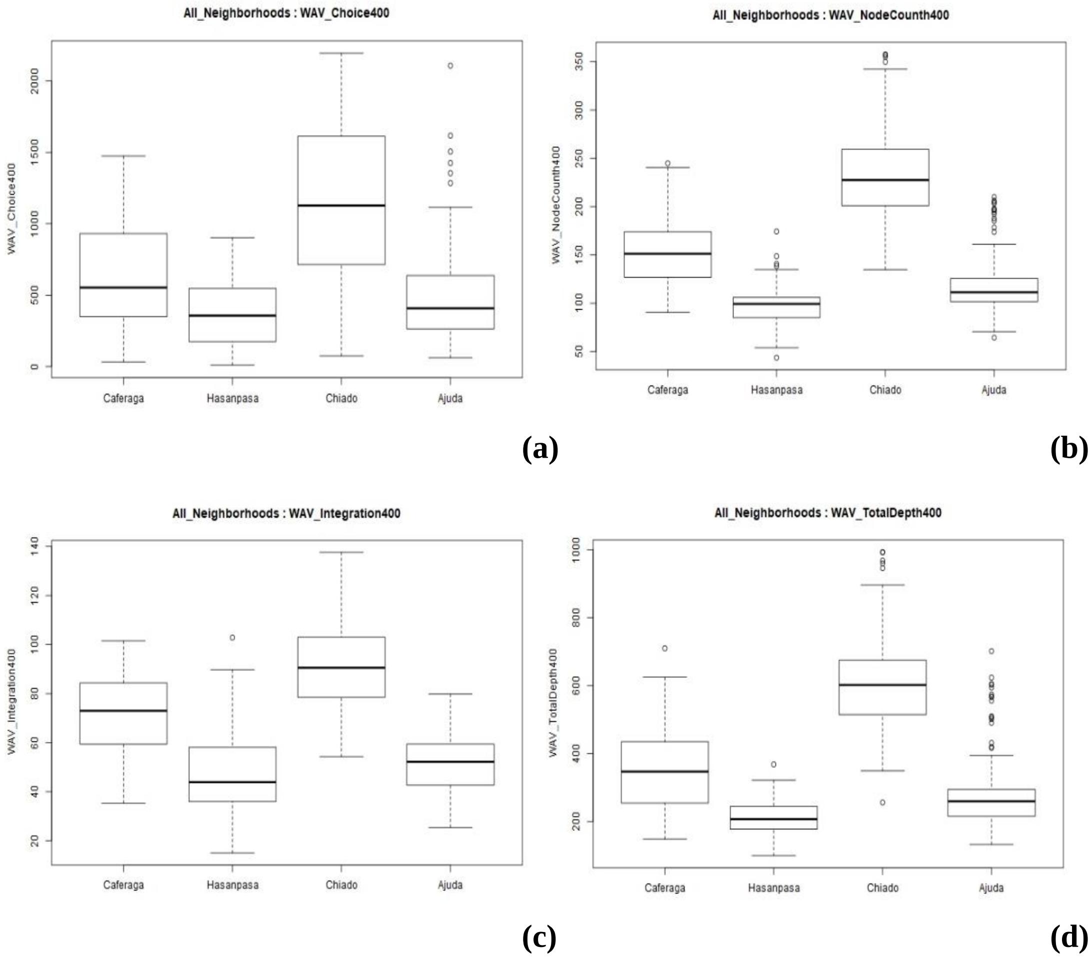


Figure 5.16 : (a) Average Choice for 400m. (b) Avg. Node Count for 400m. (c) Avg. Integration for 400m. (d) Avg. Total Depth for 400m.

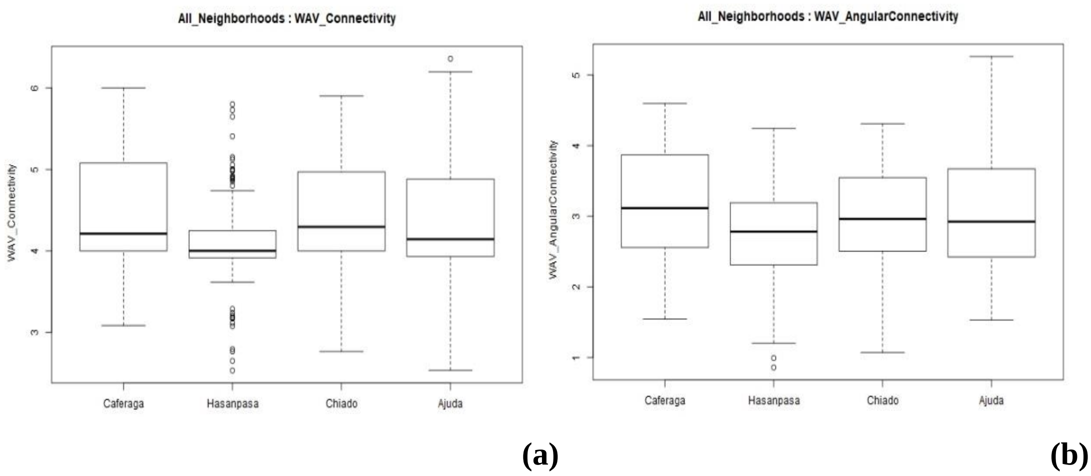


Figure 5.17 : (a) Average. Connectivity. (b) Avg. Angular Connectivity.

5.4 Streetscape Attribute Analysis Results

Maps in Appendix-F present the streetscape features that are detected using image recognition on Google Street View images acquired every 15 meters, facing both sides of the street, aggregated per Street-Void. Point value maps are also presented in Appendix-G, before aggregation. The numbers of points from which both sides of the street were analyzed per neighborhood are: 486 for Caferağa, 494 for Hasanpaşa, 633 for Chiado and 730 for Ajuda.

Sidewalk: is calculated by the average number of instances and sides at which a "pavement" was recognized on each street throughout an STV. Walkability literature has found over and over again that the existence and quality of sidewalks contribute greatly to walkability in street scale. This indicator only assesses whether a sidewalk treatment can be observed at a street side or not.

Observations: Caferağa and Chiado show better values compared to the other areas and Hasanpaşa shows lower frequency of pavements as expected (Figure 5.18).

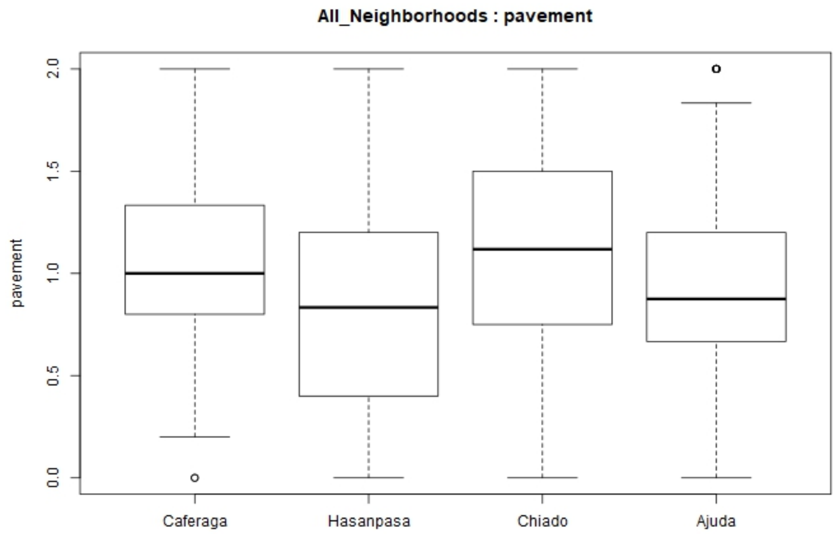


Figure 5.18 : Sidewalks.

Permeability: is calculated by the average number of windows and doors recognized on the two sides of the street throughout an STV.

Observations: Correlation of these results with assumed walkability levels seem low (Figure 5.19) but the reasons are predictable through the maps (Figures E3-E4, F5-F6). One example is that, the northern part of Caferağa area which is mostly taken up by market stalls do not have visible windows and doors yet have the highest rate of street activity due to the market. Thus, windows and doors maybe looked at where commercial activity is not distinguishable or in combination with other indicators to rule out similar situations.

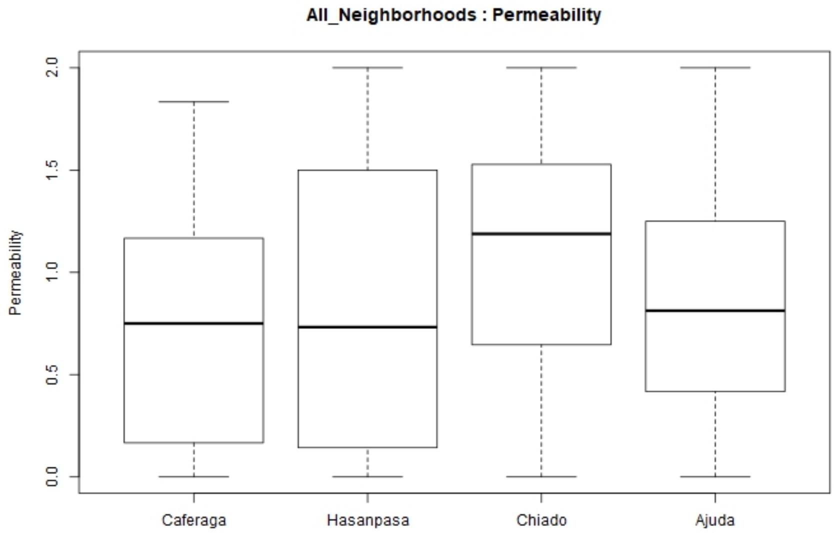


Figure 5.19 : Permeability.

Green: is calculated by instances where “landscape”, “tree”, “park” or “environment” tags were recognized.

Observations: This measure seems to negatively correlate with assumed walkability levels of neighborhoods contrary to expectation and literature findings that greenery contributes positively to walkability (Figure 5.20). However, variation of this value among streets within each neighborhood are interesting to investigate.

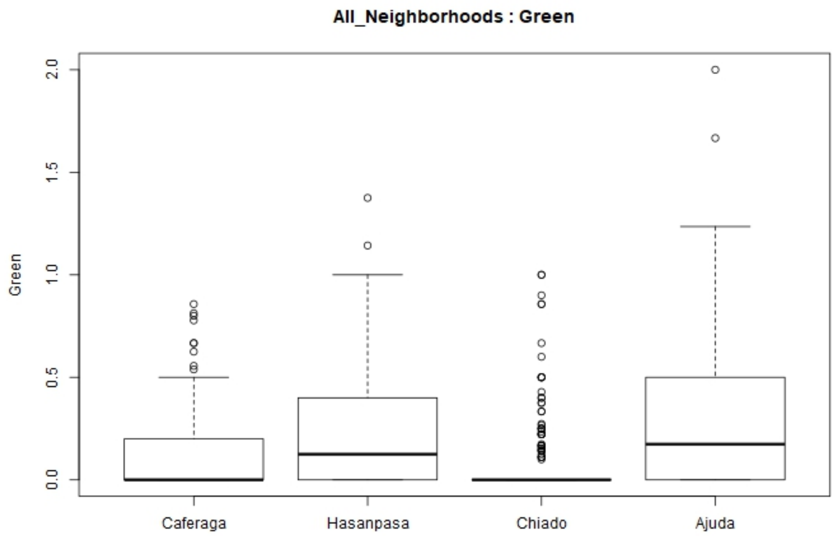


Figure 5.20 : Green.

Commercial Activity: is calculated by instances where "shopping", "commercial" or "business" tags were recognized in Google Street View images.

Observations: No obvious correlations are observed (Figure 5.21), yet a more reliable indicator of the frequency of commercial amenities is the number of Google Place locations per STV length (Figure 5.22), as these are updated by amenity owners and precisely location tagged for accessibility. If we look at Google Place frequency values, we see that they are indeed positively correlated with walkability levels of neighborhoods. Therefore, this indicator can be assumed to be better measured through Google Place locations then observable commercial activity through Google Street View images and the utilized image recognition model.

Street furniture: is calculated by instances where "chair", "bench", "table" or "furniture" tags were recognized.

Observations: This measure shows higher results for Caferağa and Chiado as is more obvious in maps as expected but variations among streets can also be investigated (Figure 5.23).

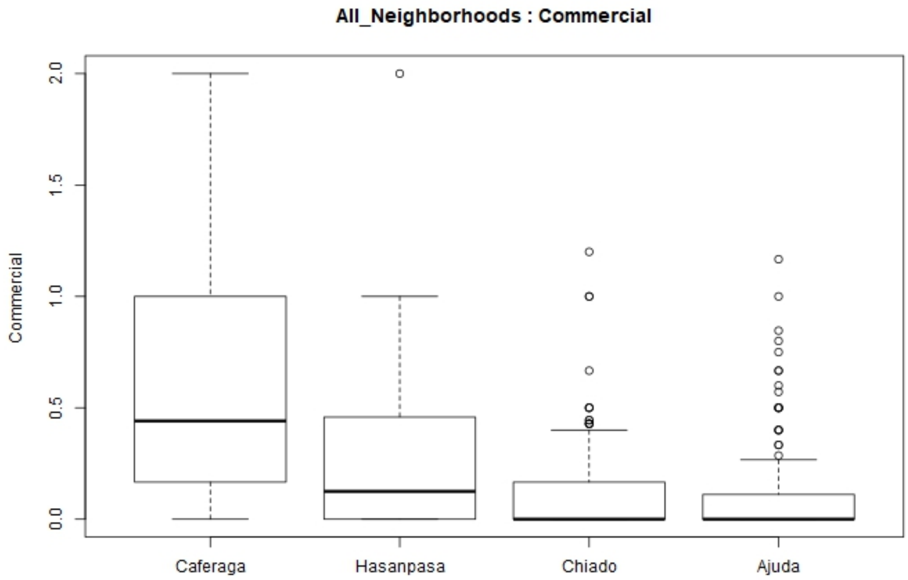


Figure 5.21 : Commercial Activity.

Motor transit: is calculated by instances where "car", "vehicle" or "traffic" tags were recognized. This is considered as an indicator of frequency of motor vehicles parked or in transit along a street and expected to have a negative impact on walkability.

Observations: All neighborhoods show high level of variation but more street activity can be correlated with lower motor traffic values, as is obvious for Caferağa and Chiado streets (Figure 5.24).

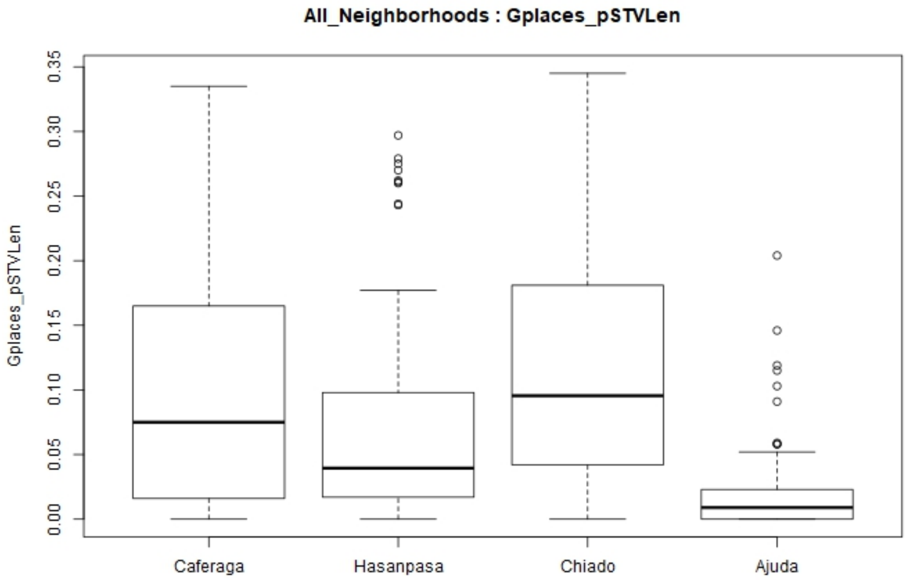


Figure 5.22 : Google Places per STV lenght.

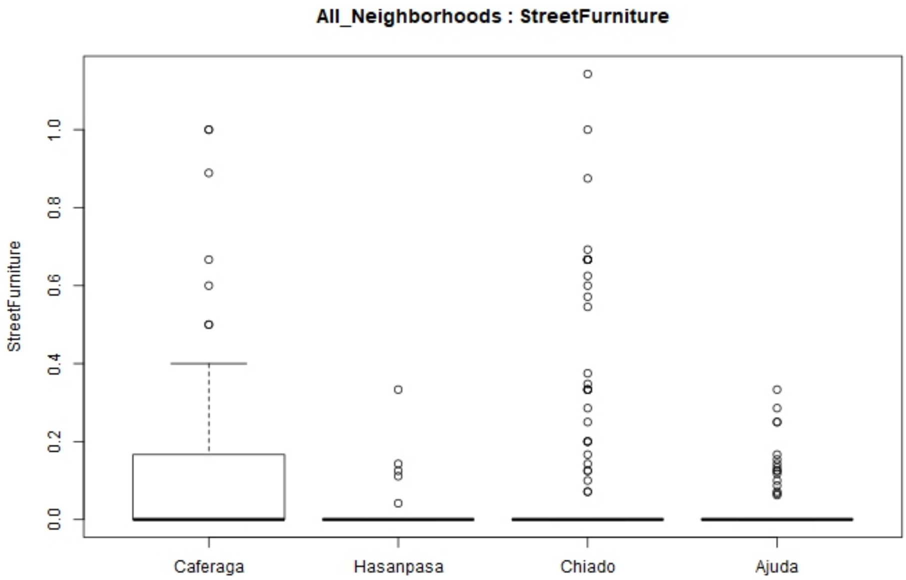


Figure 5.23 : Street furniture.

The results highlight the busiest streets by higher extreme values and streets closed to traffic by lower extremes.

Negative aspects: is calculated by instances where “calamity”, “demolition” and “abandoned” tags were recognized. These are expected to contribute negatively to walkability.

Observations: The results show higher values in Hasanpaşa and Ajuda as expected (Figure 5.25).

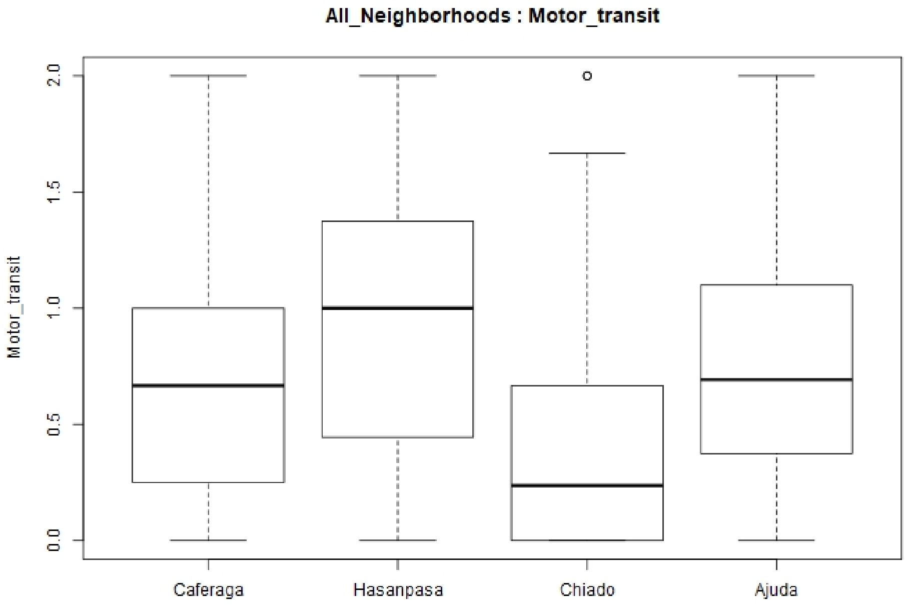


Figure 5.24 : Motor transit.

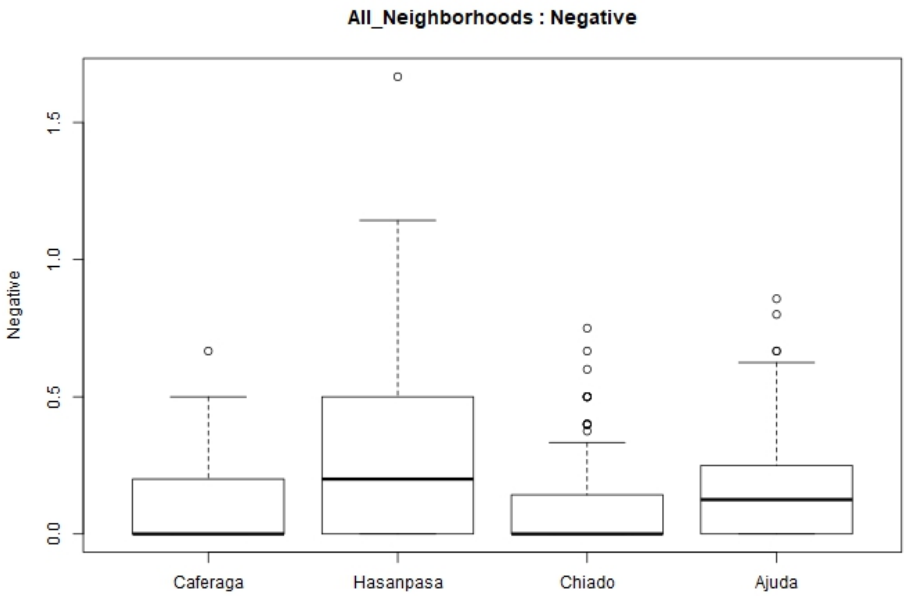


Figure 5.25 : Negative aspects.

5.5 Grouping and Conclusions Based on Initial Observations

Table 5.4 presents the measured walkability attributes that have been described in detail previously. The attributes are grouped under characteristics which have also already been explained in detail. Brief explanations are provided for easier reference in the table as well.

Table 5.4 : Grouped indicators.

Characteristic	Attribute	Explanation
Density		
Physical	**STV_BArea_p_STVLen**	Total footprint area of surrounding buildings per STV length.
	STV_BArea_p_STVArea	Total footprint area of surrounding buildings per STV area.
	STV_FArea_p_STVLen	Total floor area of surrounding buildings per STV length.
	STV_FArea_p_STVArea	Total floor area of surrounding buildings per STV area.
Use	**GPlaces_pSTVLen**	Number of Google Place locations that are tagged within 3.5 meters of the STV footprint area divided by the length of STV.
Diversity		
Morphological	**STVs_#FacadesPerM**	Number of surrounding Facades per STV length.
	Cov_CSCompactness	Coefficient of variation of included CS Compactnesses per STV.
	Cov_CSSquareness	Coefficient of variation of included CS Squarenesses per STV.
	Cov_CSSkyview	Coefficient of variation of included CS Skyview factors per STV.
	Cov_CSElevation	Coefficient of variation of included CS Elevations per STV.
	Cov_CSDiameter	Coefficient of variation of included CS's largest inscribed circle diameters per STV.
	Cov_#Floors	Coefficient of variation of building floor numbers per STV.
	Cov_BArea	Coefficient of variation of building footprint areas per STV.
	Cov_FArea	Coefficient of variation of building floor areas per STV.
Land use	**GPlaces_pSTVLen**	Number of Google Place locations that are tagged within 3.5 meters of the STV footprint area divided by the length of STV.
Based on municipal data	**Not measured:** non observable data	
Connectedness		
Space Syntax	**WAv_AngularConnectivity**	Weighted average of angular connectivity.
	WAv_Connectivity	Weighted average of connectivity.
	WAv_Choice400	Weighted average of Choice within 400 m radius.
	WAv_Integration400	Weighted average of integration within 400 m radius.
	WAv_NodeCount400	Weighted average of node count within 400 m radius.
	WAv_TotalDepth400	Weighted average of total depth within 400 m radius.

Table 5.4 (continued) : Grouped indicators.

Characteristic	Attribute	Explanation
(Human) Scale		
	STVs_Area	Footprint area of STV (not projected)
	STVs_Length	Length of STV. Length of longest continuous street segment.
	STVs_Width	Average width of STV. STV area divided by length.
	STVs_Height	Weighted average of heights of included CVs.
	STVs_#FacadesPerM	Number of Facades per STV length.
	WAV_FacadeArea	Weighted average of building and wall façade areas surrounding STV.
	WAV_FacadeWidth	Weighted average of building and wall façade widths surrounding STV.
	WAV_FacadeHeight	Weighted average of building and wall façade heights surrounding STV.
	Avg_Floors	Average number of building floors per STV.
	AV_BArea	Average footprint area of surrounding buildings per STV.
	AV_FArea	Average of floor area of surrounding buildings per STV.
Complexity		
Granularity/ Articulation	**STVs_#FacadesPerM**	Number of Facades per STV length.
	B#_p_STV_Len	Number of surrounding buildings per STV length.
	FlowLength/STVArea	Total length of included Flows divided by STV area.
	WAV_FacadeArea	Weighted average of building and wall façade areas surrounding STV.
	WAV_FacadeWidth	Weighted average of building and wall façade widths surrounding STV.
	STVs_PerimArea	Perimeter of an STV divided by its Area
Other streetscape features	**green**	Number of street sides where trees, parks, natural greenery or landscape is identifiable
	permeability	Number of street sides where doors or windows are identifiable
(-)	**motor**	Number of street sides where cars, vehicles or traffic is identifiable
	commercial	Number of street sides where commerce, shopping amenities or businesses is identifiable
commercial amenities	**GPlaces_pSTVLen**	Number of Google Place locations that are tagged within 3.5 meters of the STV footprint area divided by the length of STV.
	street_furniture	Number of street sides where chairs, benches or other furniture is identifiable

Table 5.4 (continued) : Grouped indicators.

Characteristic	Attribute	Explanation
Enclosure		
	STVs_Height	Weighted average of heights of included CVs.
	STVs_Height/Width	STV_Height divided by STV_Width
	STVs_Enclosure	Proportion of total Façade width to perimeter.
	WAV_FacadeHeight/Width	Weighted average of building and wall façade height to width proportions
	WAV_CS_Skyview	Weighted average of included CS Sky view factors per STV.
Shape		
	STVs_Compactness	Ratio between the perimeter of STV footprint and perimeter of a circle of the same area.
	WAV_CS_Compactness	Weighted average of included CS Compactnesses per STV.
	WAV_CS_Squareness	Weighted average of included CS Squarenesses per STV.
	STVs_PerimArea	Perimeter of an STV divided by its Area
Inclination		
	WAV_FlowIncline	Weighted average of slope of Flows within STV.
	STVs_ElevationChange	Change in elevation within an STV.
	Cov_CSElevation	Coefficient of variation of included CS Elevations per STV.
Permeability/ Transparency		
	permeability	Number of street sides where doors or windows are identifiable
	commercial	Number of street sides where commerce, shopping amenities or businesses is identifiable
	GPlaces_pSTVLen	Number of Google Place locations that are tagged within 3.5 meters of the STV footprint area divided by the length of STV.
Infrastructure Quality (and Maintenance)		
	green	Number of street sides where trees, parks, natural greenery or landscape is identifiable
	pavement	Number of street sides where pavements are identifiable
	street_furniture	Number of street sides where chairs, benches or other furniture is identifiable
	motor_transit	Number of street sides where cars, vehicles or traffic is identifiable
	negative	Number of street sides where abandonment, demolition or calamity is identifiable

Based on this grouping and initial observations, we can say that the majority of attributes measurable through the proposed workflow that are grouped under the characteristics of Density, Connectedness, Human Scale and Enclosure seem to correlate with assumed walkability levels of neighborhoods, a part of the attributes grouped under the characteristic of Complexity seem correlated with levels of walkability and attributes under the characteristics of Shape, Inclination, Permeability and Infrastructure Quality are measured to show low correlations with the compared levels of walkability for the studied neighborhoods.

These initial findings before further statistical analysis reveal that several morphological and streetscape measures utilized in literature have a more complex relationship with the walkability of streets than they are assumed to be. Many indicators commonly accepted in literature, especially 2d ones including that of Space Syntax, street wall continuity based on footprints of buildings along streets and street-widths are revealed to be oversimplified indicators for walkability when we consider their results alongside other indicators, we have utilized in these case studies. Some new indicators such as Compactness, Squareness, Perimeter/Area and ones that already appear in literature but are measured by new methods are proposed within this study. Additionally, new relationships are investigated such as diversity to be linked by variations in morphological characteristics even though this measure does not align with expectations.

One of the findings of this research, that begin to be apparent in these initial observations is that, several attributes and characteristics that appear in literature and are now commonly accepted indicators of walkability can actually be measured remotely with the semi-automated measuring method proposed, without the requirement of on-site audits and surveys, yielding similar results. The descriptive analysis results of these indicators presented in maps and boxplots align with presumed walkability levels of the four neighborhoods. Even though a precise comparison of these values of the streets studied with each other within each neighborhood is yet to be investigated in the following chapters, the ranges and median values of the results align with expectations for several indicators mentioned above in Caferağa and Chiado compared to Hasanpaşa and Ajuda, as is presumed walkability and street activity.

The measures that do not show obvious correlations with expected levels of walkability at current level of detail in visualizations and require further study are as follows:

Weighted Average of Flow Inclines: This indicator represents the average inclination of streets, and is not expected to be directly correlated with how walkable or not walkable a neighborhood is. However, when different levels of walkability are considered, higher inclinations do restrict pedestrians of different physical abilities such as the wheelchaired and the elderly.

Observations: No direct correlations with assumed walkability of neighborhoods were expected or observed (Figure 5.26).

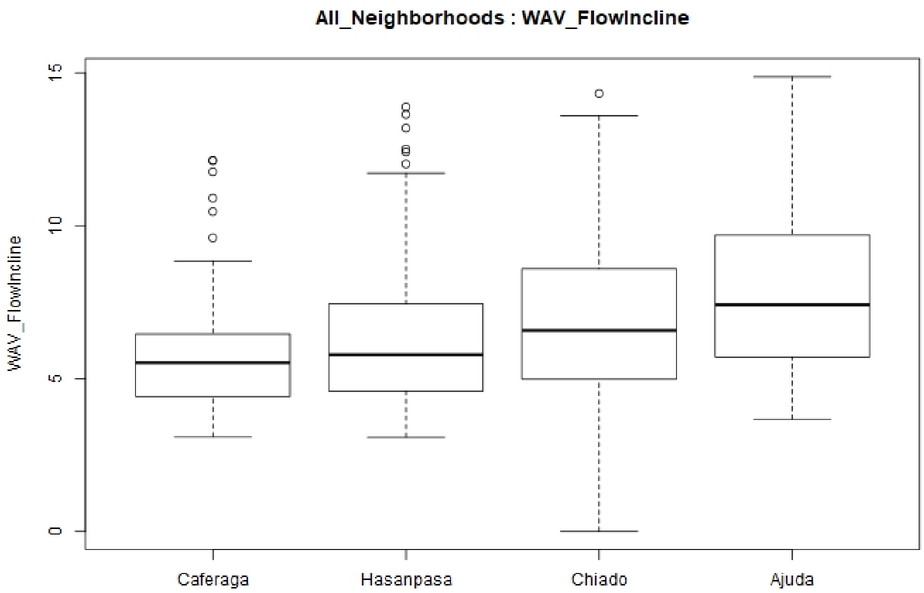


Figure 5.26 : Average flow inclines.

Number of Facades per STVLen: This measure shows the level of articulation or frequency of change in the size and form of surrounding limits of a street space. It may point to a more visually diverse and attractive environment; it may also be correlated with higher number of building facades per street length. This may open up more opportunity for diverse functions on a street therefore contribute to walkability in a positive way.

Observations: The results of this measure do not show an obvious correlation with walkability therefore it should be studied further (Figure 5.27).

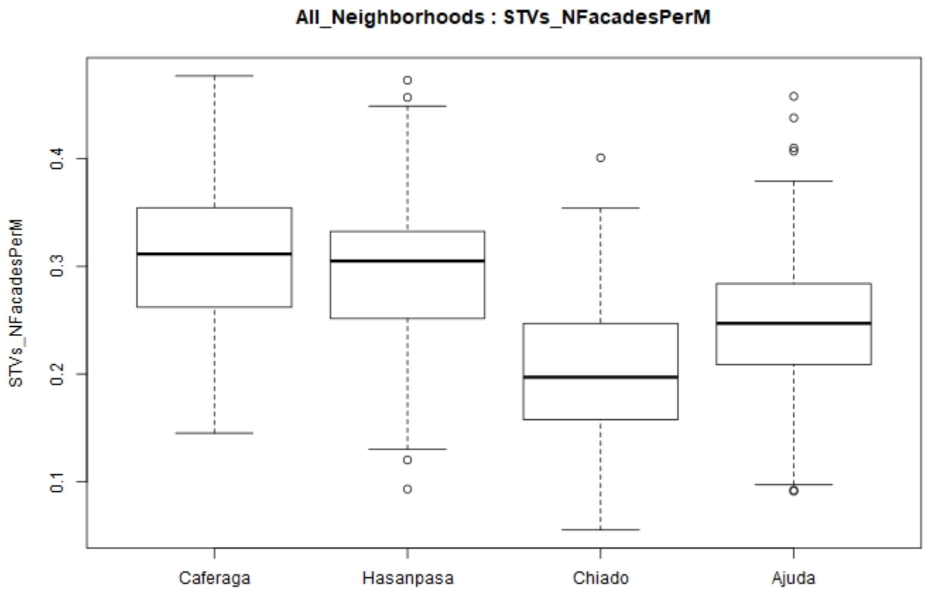


Figure 5.27 : Number of facades per STV length.

Elevation Change: This measures the difference between the maximum and minimum elevation within an STV. Such a measure is not correlated with walkability in literature, yet it is investigated in this thesis as a possible contributor to scenic views that may enhance visual complexity and, in some cases, may correlate with higher or lower levels of enclosure.

Observations: The results do not show obvious correlations with assumed levels of walkability (Figure 5.28) but the indicator can be investigated further. One instance where the high levels of this value can be seen in Chiado is around the Santa Catarina viewpoint (see Figure C.32), which is already known for its scenic views and that attracts a lot of activity as an urban point of interest. On the other hand, this measure is correlated with the length of the street and therefore shows higher values for longer streets as obvious in Hasanpaşa. Nevertheless, it is investigated as a separate measure than Flow Inclination so the elevation change is not divided by the STV Length.

STV Compactness: Calculated by dividing the circumferences of circles having the same area as STV footprints by the STV perimeters, this indicator helps distinguish between thin, long and highly articulated streets and square-like spaces in the urban network. Higher values may indicate less articulation therefore translate to less complexity and diversity, resulting in lower walkability. On the other hand, for smaller urban spaces like neighborhood-scale squares, compactness could indicate better visibility of all parts of the space, therefore enhancing the feeling of safety and contributing to walkability in a positive way. This indicator distinguishes between square and street-like spaces.

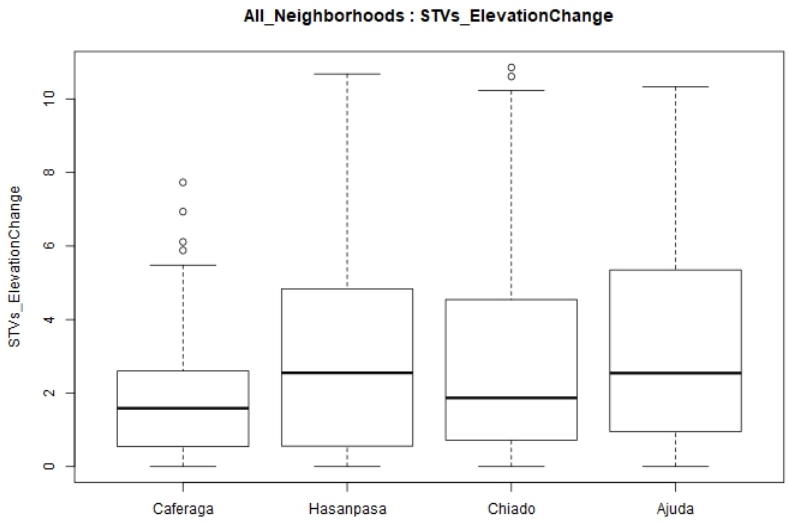


Figure 5.28 : Elevation change.

Observations: As it is also possible to see on the maps of the areas studied, Chiado has the highest number of squares, therefore resulting in higher values of compactness for the STVs and Caferağa has mostly thin and long streets with low compactness values (Figure 5.29). While not translating into an assumption regarding relative walkability levels of neighborhoods, the results support the need for the combined study of some indicator results to get an understanding of the complex nature of urban morphology and its influence on walkability.

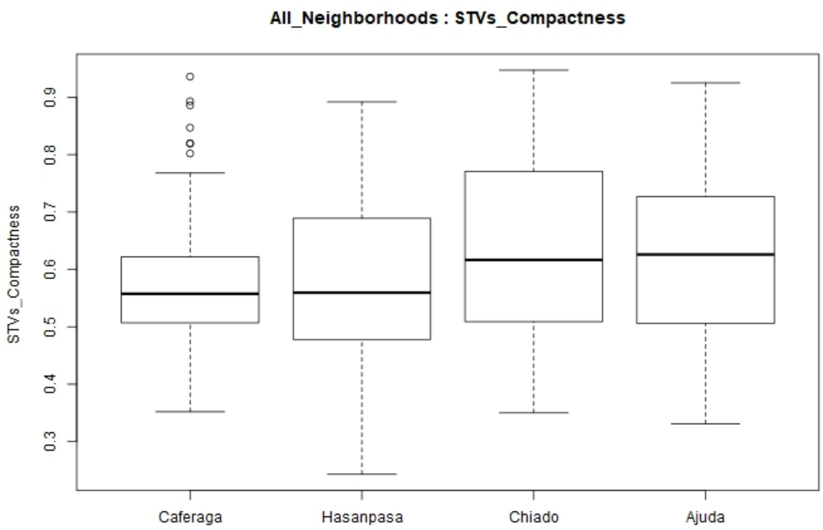


Figure 5.29 : STV Compactness values.

Weighted Average of CV Compactness: Calculated by taking the weighted average of the CV Compactness values, this indicator is concerned with the shape and level of articulation of unit spaces within an STV, similar with the Perimeter/Area indicator. The difference between this indicator and the STVs_Compactness indicator is that, this indicator looks at an average value for how compact the unit spaces within a whole street segment space (STV) are, rather than how compact the whole street segment space is. This indicator can be considered together with the STVs_Width and STVs_Compactness indicators to first distinguish between the squares and streets (if width and compactness values are high, it is more likely to be a square) and then to look at how articulated spaces within the street or square is.

Observations: No obvious correlations can be observed from the maps and the boxplot with assumed walkability levels of neighborhoods (Figure 5.30) but this indicator will be further evaluated.

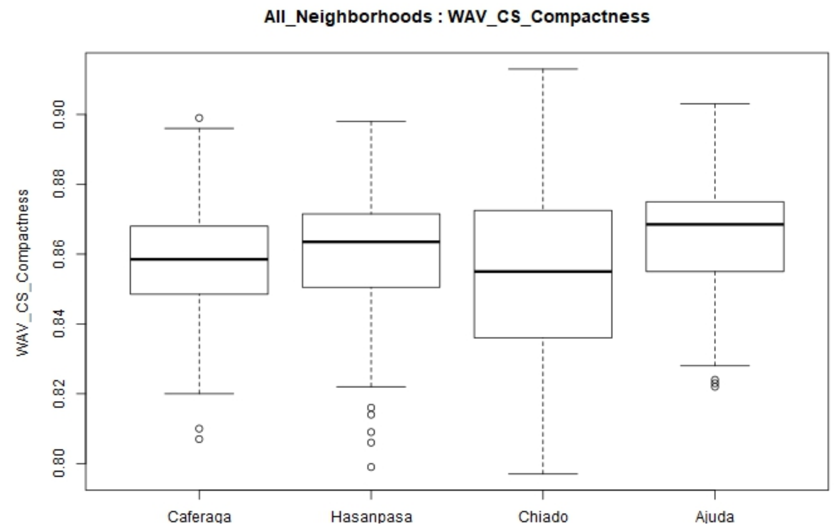


Figure 5.30 : Averages of Convex Space Compactness values per STV.

Weighted Average of CV Squareness: Obtained by taking the weighted average of the area of the smallest bounding square divided by the area of a CV, this measure looks at how close to a square the unit areas constituting the STV are in terms of shape. No known relationships of such an attribute is found in literature therefore no correlations are assumed with walkability levels. However, closeness to a square in shape may translate to better visibility in smaller neighborhood squares, and thus to better sense of safety contributing to walkability.

Observations: No obvious correlations are observed but the indicator can be investigated in more detail (Figure 5.31).

Coefficient of Variation of Building Area and Floor Area: tell us the levels of variation in building footprint and total floor areas surrounding an STV. These measures can be taught to have a positive correlation with walkability, as frequent change in building sizes make it more likely that the forms, facades and possibly the functions of buildings will be diverse, therefore the potential for a variety of uses and activities as well as the street façade to be more interesting and attractive is higher.

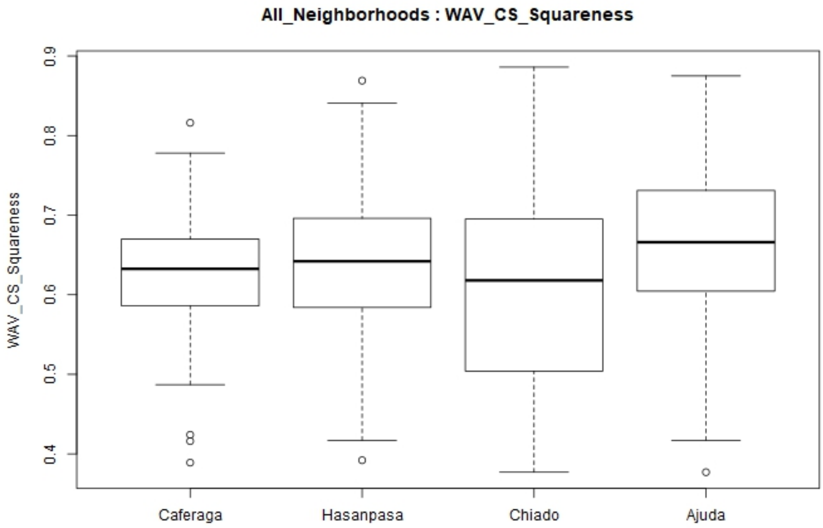


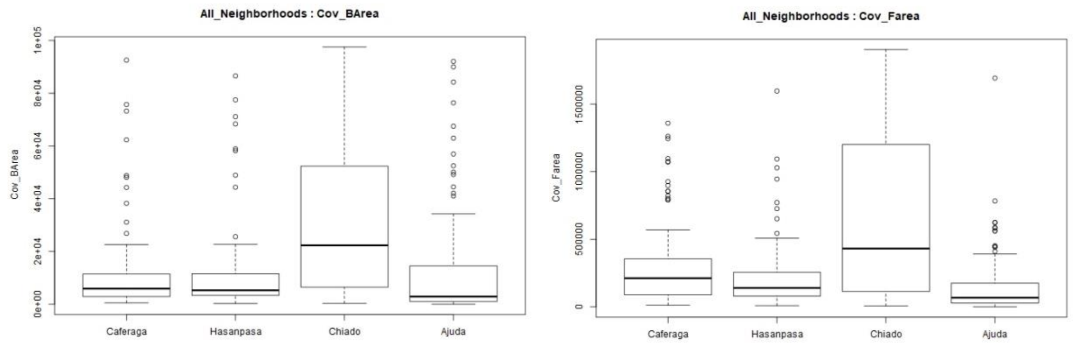
Figure 5.31 : Averages of Convex Space Squareness values per STV.

On the other hand, smaller average building footprint and floor areas could also mean higher number of buildings per street length and therefore more opportunity for diverse facades and uses within a length of street.

Observations: This value seems to be higher in Lisbon compared to Istanbul but don't show any obvious relationship with overall walkability levels (Figure 5.32), therefore it should be investigated further.

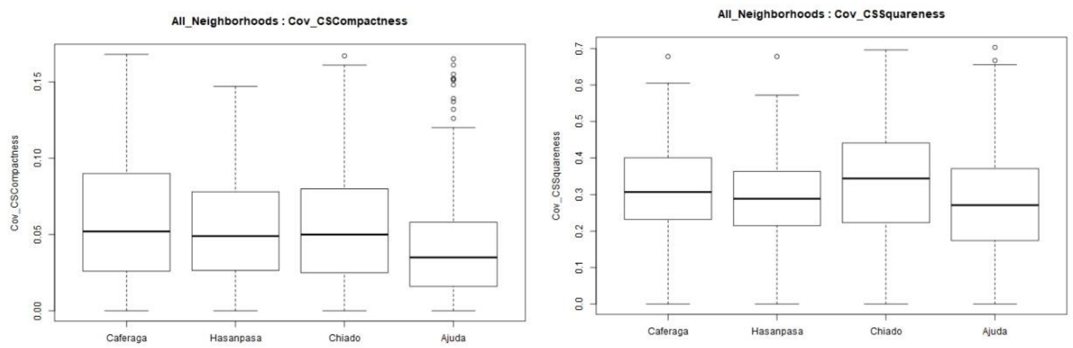
Coefficient of variation of CS_Squareness, CS_Compactness, CS_SkyView, CSElevation, CS_Number of Floors, CS_Diameter: These indicators are developed and tested in this thesis as possible measures of morphological diversity. They indicate the level of variance of each of these indicators throughout the unit spaces within STVs.

Observations: No obvious correlations are immediately observable, however **Cov_Skyview** and **Cov_Squareness** values seem to be higher in Caferağa and Chiado which are more walkable neighborhoods (Figures 5.33-5.34).



(a) **(b)**

Figure 5.32 : (a) Cov of building areas. (b) Cov of floor areas.



(a) **(b)**

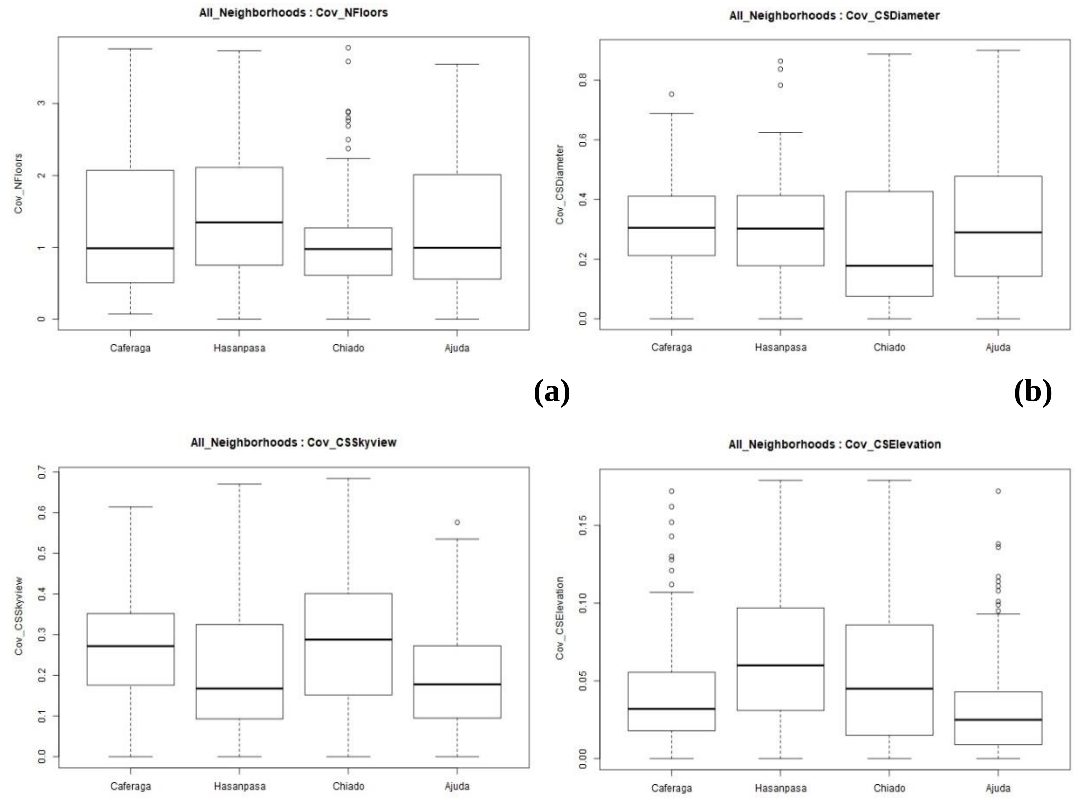
Figure 5.33 : (a) Cov of CS Compactness values. (b) Cov of CS Squareness values.

The measures presented in this section will be compared against the activity indicators (Table 5.5) which are used as a proxy for walking behavior in this thesis. These indicators are Flickr and Instagram posts per STV Length and average number of street sides (ANSS) where people are identifiable on Google Street View images for each STV.

Table 5.5. : Activity Indicators.

Indicator of activity (walking activity)		
	Flickr_pSTVLen	Number of Flickr posts geo-tagged within 3.5 meters of the STV footprint area divided by the length of STV.
	InstagramPosts_pSTVLen	Total number of Instagram posts linked to locations geo-tagged within 3.5 meters of the STV footprint area divided by the length of STV.
	people	Average number of street sides where people identifiable per STV.

As seen in maps (Figure H.3-H.8) and boxplots (Figure 5.35-5.36) of these indicators, Flickr and Instagram post frequency seems to be highly correlational with the compared levels of walkability between neighborhoods yet the average number of street sides with people only shows expected differences relatively between Caferağa and Hasanpaşa, and between Chiado and Ajuda (Figure 5.37).



(a) (b)

(b) (d)

Figure 5.34 : (a) Cov of number of floors. (b) Cov of CS diameters. (c) Cov of CV Skyview Factor values. (d) Cov of Convex Space elevation values.

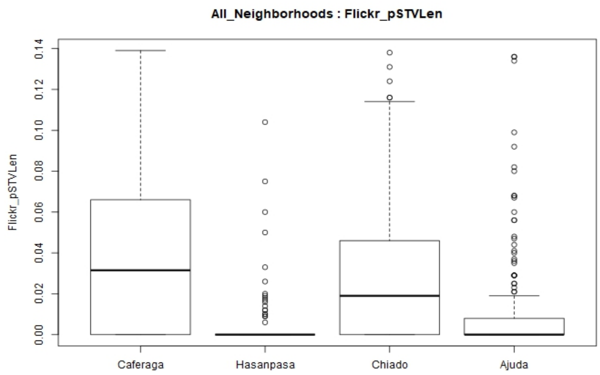


Figure 5.35 : Number of Flickr posts per STV length.

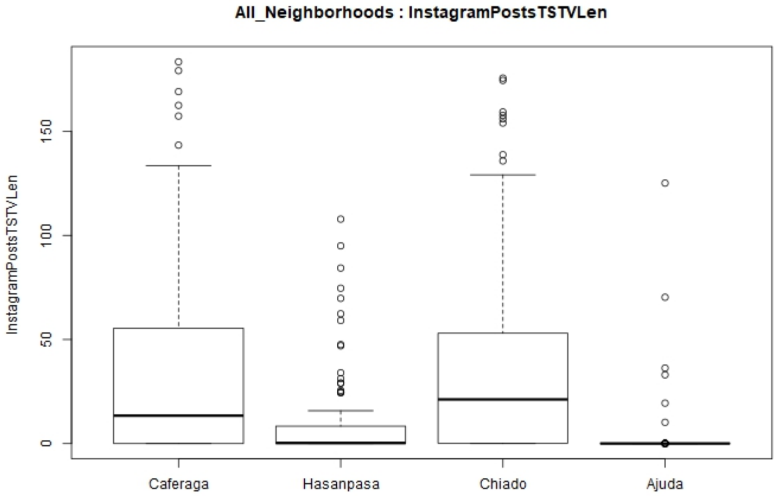


Figure 5.36 : Number of Instagram posts per STV length.

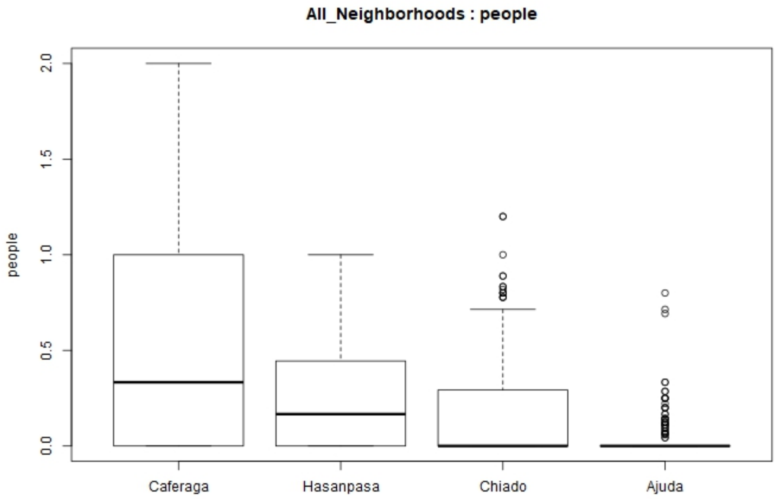


Figure 5.37 : ANSS where people are identified.

6. FURTHER ANALYSIS

In this chapter, we further explore our dataset through statistical methods in order to understand whether and how our proposed attributes' measures are expressed in real life, on the street. Through regression analysis, we test if these attributes can predict how preferable streets are for walking, assuming walkability is represented by social media and google street view data. Then, we use k-means clustering to classify our street space samples and compare their tangible, experienced characteristics with their attributes' behavior. These analyses help identify distinguishing attributes for streets of different characteristics, and also show how some attribute measures can be inconsistent with the way that phenomenon is actually experienced on the street and contradictory to well established literature, in which case we go back and evaluate their means of quantifying a feature and their effectiveness. Ultimately, this part of the study is used for reducing the tested attributes to a set of more reliable and effective attributes for measuring walkability. It also informs which attributes should be utilized to first classify street samples, and then how different sets of appropriate attributes and value thresholds should be used to further analyze them for walkability.

6.1 Can Our Morphological and Streetscape Attributes Predict Walkability?

The walkability measuring methods in literature commonly test a set of measured attributes in terms of how predictive they are for a specific measurable indicator of walkability. This indicator can be people counts, collected by counting people walking on the site using certain pre-defined protocols, or tracking people's movements in the city using video cameras or based on GSM data taken from their smart phones within a time frame (Vanky, 2017). Recently, location tagged social media posts (Quercia et al., 2015) as well as people counts on open maps' street view images (L. Yin et al., 2015) have been used as indicators for how popular certain streets are, to help interpret how the built environment affects people's preferences for occupying certain streets. If this indicator data is consistent and representative enough, it can help identify which measurable built environment attributes are the most strongly correlated with how walkable streets are and therefore can inform design decisions with quantitative evidence.

In this part of the study, we test whether Flickr post frequencies, Instagram post point frequencies and the average number of street sides where people are seen on Google Street View images within our studied context can be used as indicators of walkability and help assess which of our attributes are more determining for walking behavior on streets. For this, we try to predict these attribute values as outcome variables with our morphological and streetscape attributes introduced in the previous chapter using a regression model. Also, the social media and people count indicators were scaled and added together to create what we call “a combined popularity indicator” and tested with the predictive model. Thus, the questions investigated in this section are:

1- How representative are our walkability-related built environment and streetscape variables in predicting the social media post frequencies and street view-based people counts?

2- If the attributes are representative in predicting these values, can the social media frequency variable, people count variable or a variable created by combining them represent how walkable a street is?

3- If they can, can we measure walkability using our attributes and which of our attributes have the greatest impacts; thus, should be utilized to evaluate and improve walkability?

We answer these questions by comparing the findings of our preliminary literature study, the results of the predictive regression model and our descriptive analysis results of samples grouped based on neighborhoods and clusters. Neighborhood-based groups and their descriptive analysis were presented in the previous chapter and a comparison of clusters of these samples derived using a k-means algorithm will be presented later in this chapter.

For the regression analysis, a number of models were explored seeking to identify the levels of impact of indicators in determining the outcome variable. Four outcome variables were tested separately with these predictors: Flickr_pSTVLen, InstagramPoints_pSTVLen, people, and the combined popularity variable (comb). A set of indicators were selected firstly based on the significant differences of the median and range values between neighborhoods considered walkable (Caferağa and Chiado) and not walkable (Ajuda and Hasanpaşa) (Figures 5.1-5.29), then based on their indicator's representativeness within the set and finally for their theoretical significance. For example, we would like to explore the impacts of STVs_Width and STVs_Height separately so we keep both but eliminate STVs_HeightTWidth variable. The following list of attributes were initially selected as predictors: STVs_Length, STVs_Width, STVs_Height, STVs_PerimTArea, FlowLengthTSTVArea, WAV_FlowIncline, STVs_NFacadesPerM, WAV_FacadeWidth, WAV_FacadeHeight, STVs_ElevationChange, WAV_CS_Skyview, BN_pSTV_Len, AV_Floors, BArea_pSTVLen, AV_BArea, FArea_pSTVLen, WAV_Integration400, WAV_NodeCount400, pavement, Permeability, Green, Commercial, Negative, Motor_transit, Gplaces_pSTVLen and STVs_Compactness. Then highly correlated variables (those with absolute correlation greater than 0.75) were determined which were STVs_Width, FArea_pSTVLen, WAV_FacadeHeight and WAV_Integration400. We removed FArea_pSTVLen and WAV_FacadeHeight but since we consider STVs_Width and WAV_Integration400 important variables to keep, we removed the variables highly correlated with them which were STVs_PerimTArea and WAV_FlowIncline (with STVs_Width) and WAV_NodeCount400 (with WAV_Integration400). Then we standardized and transformed the predictors. We randomly set aside 20% of the observations as test set and used the remainder 80% for model training. 5 models under consideration were: Linear regression, Ridge regression, Lasso regression, Elastic Net regression and Multivariate Adaptive Regression Splines (MARS) and Generalized Additive Model (GAM). To obtain the optimal tuning parameters, each model except linear regression underwent through 10 separate 5-fold cross-validation.

Given the fitted models, we first predicted the **people** variable on the test set and found that the linear regression gave the lowest root mean square error (RMSE). We later looked at the variable importance of the final model and found that: **Commercial, Permeability, Motor_transit, WAV_Integration400** and **Green** were the most predictive; with Permeability, Motor_transit and Green to have a negative impact on the outcome. The impact of the next most important variables can be seen in Table 6.1 based on the t-statistic values in Table 6.2: **STVs_ElevationChange, pavement, STVs_NFacadesPerM, STVs_Width** and **Negative** with STVs_ElevationChange, pavement, STVs_Compactness and AV_BArea having negative impacts looking at the estimate coefficient signs. Among these, Permeability, pavement, Green and STVs_Compactness are unexpected negative coefficient values.

Table 6.1 : Variable importance of top 15 variables for people.

Variable	Importance
Commercial	100.000
Permeability	40.073
Motor_transit	38.60
WAV_Integration400	16.374
Green	14.624
STVs_ElevationChange	12.82
pavement	12.745
STVs_NFacadesPerM	12.30
STVs_Width	8.214
Negative	7.863
BArea_pSTVLen	6.713
STVs_Compactness	6.482
AV_BArea	5.427
FlowLengthTSTVArea	4.26
AV_Floors	3.73

Predicting the **Flickr_pSTVsLen variable**, we calculated the MARS model to have the lowest RMSE. In this model, only three predictive variables were found to be important in the following order: **STVs_Width, Commercial and WAV_Integration400** (Table 6.3).

However, the MARS model indicated that the STVs_Width variable only has predictive power of 0.65 when it is above 30.737 (centered, scaled and transformed value: 1.8033), Commercial variable only has predictive power of 1.87 when it is above 1 (centered, scaled and transformed value: 1.8765) and WAV_Integration400 has a negative predictive coefficient of -0,03 when it is below 122.50 (centered, scaled and transformed value: 1.8723) (Table 6.4). This means the STVs_Width can only predict Flickr values when the street is wider than 30.7 meters accounting for a very small percentage of the samples, and then Flickr values are positively correlated with the street width; Commercial variable becomes predictive when it is greater than 1 which accounts for about 10% of the samples and Integration is negatively correlated with Flickr values when it is below 122.5, as it is for more than 95% of samples.

Table 6.2 : Variable estimate, std. error, t-statistic and p.values for people.

term	estimate	std.error	t-statistic	p.value
(Intercept)	0.245684	0.010165	24.169539	0.000000
STVs_Length	-0.002040	0.037551	-0.054350	0.956679
STVs_Width	0.055853	0.038387	1.454973	0.146378
STVs_Height	-0.006806	0.024142	-0.281907	0.778145
FlowLengthTSTVArea	0.017918	0.022953	0.780656	0.435418
STVs_NFacadesPerM	0.029984	0.013938	2.151255	0.031991
WAV_FacadeWidth	-0.008547	0.016508	-0.517746	0.604891
STVs_ElevationChange	-0.032129	0.014340	-2.240407	0.025555
WAV_CS_Skyview	0.002280	0.028754	0.079318	0.936814
BN_pSTV_Len	-0.025799	0.043100	-0.598592	0.549748
AV_Floors	0.012174	0.017633	0.690431	0.490281
BArea_pSTVLen	0.054651	0.045580	1.199008	0.231159
AV_BArea	-0.046551	0.047512	-0.979770	0.327729
WAV_Integration400	0.042718	0.015006	2.846585	0.004622
pavement	-0.027930	0.012538	-2.227635	0.026401
Permeability	-0.120515	0.017497	-6.887779	0.000000
Green	-0.036954	0.014503	-2.548029	0.011166
Commercial	0.243864	0.014255	17.10670	0.000000
Negative	0.015983	0.011455	1.395195	0.163649
Motor_transit	-0.100538	0.015150	-6.636137	0.000000
Gplaces_pSTVLen	-0.001243	0.014021	-0.088693	0.929365
STVs_Compactness	-0.049369	0.042573	-1.159640	0.246814

These results show that within our samples, Flickr cannot reliably represent walking behavior as even the most significant predictors are only correlated with a small percentage of samples' Flickr values and show counter intuitive relationships: STVs_Width would be expected to negatively correlate with walkability especially when street spaces become as wide as 30 meters and Integration has been proven to correlate positively with walkability along with other Space Syntax variables in several studies (Özbil et al., 2015) while it has a negative coefficient in the model.

Predicting the **InstagramPoints_pSTVLen** variable, we again calculated the MARS model to have the lowest RMSE. In this model, only four predictive variables were found to be important: **GPlaces_pSTVLen, WAV_Integration400, STVs_Height** and **STVs_Width** (Table 6.5).

Table 6.3 : Variable importance for Flickr_pSTVLen.

Variable	Importance
STVs_Width	**100.00**
Commercial	73.64
WAV_Integration400	40.48

Table 6.4 : Variable coefficients for Flickr_pSTVLen.

Variable	coefficient
(Intercept)	0.10368312
h(STVs_Width-1.80332)	0.65017690
h(Commercial-1.87655)	0.13076343
h(1.87236-WAV_Integration400)	-0.03259657

The coefficient values indicate that Gplaces_pSTVLen variable has a positive correlation with Instagram Point frequencies with a coefficient of 0.11 only when it is above 0.205 (centered, scaled and transformed value: 0.7752) which accounts for about 20% of the samples and a negative correlation coefficient of -0.079 if it is below 0.205 (Table 6.6). STVs_Height, STVs_Width and WAV_Integration400 values are correlated with Instagram point frequencies only in conjunction with Google Place frequencies. When Google Place frequencies are below 0.205, they do not have predictive power. Within the small number of samples that Instagram Point frequencies can be partially predicted, Integration and street widths have positive correlations with Instagram Point frequencies and street space heights have a negative correlation. Integration aligns with, whereas STV width and heights contradict with expectations based on literature. These results show that Instagram Point frequencies cannot reliably represent walking behavior for predictive analysis.

Table 6.5 : Variable importance for InstagramPoints_pSTVLen.

Variable	Importance
Gplaces_pSTVLen	**100.00**
WAV_Integration400	100.00
STVs_Height	24.81
STVs_Width	16.57

Table 6.6 : Variable coefficients for InstagramPoints_pSTVLen.

(Intercept)	**0.122**
h(Gplaces_pSTVLen-0.775213)	0.1137
h(0.775213-Gplaces_pSTVLen)	-0.0795
h(1.01378-WAV_Integration400) * h(Gplaces_pSTVLen-0.775213)	0.0507
h(STVs_Height- -1.3063) * h(Gplaces_pSTVLen-0.775213)	-0.0555
h(STVs_Width-0.17915) * h(Gplaces_pSTVLen-0.775213)	0.0472

And finally predicting the **combined popularity** variable, once again the MARS model was found to have the lowest RMSE. In this model, only six predictive variables were found to be important: **GPlaces_pSTVLen, Commercial, STVs_Width, Permeability, BArea_pSTVLen** and **Motor_transit** (Table 6.7).

Not surprisingly, considering that this variable combines the people, Flickr and Instagram values, the coefficients for the combined variable (Table 6.8) show similar patterns. Almost all significant predictors have predictive power above certain thresholds: Commercial is positively correlated when it is above 0.846 (centered, scaled and transformed value: 1.497) and STVs_Width is positively correlated when it is above 32.151 (centered, scaled and transformed value: 1.863). Permeability, Motor_transit and BArea_pSTVLen are negatively correlated above certain threshold values. Among these, building areas and motor transit indicators having negative correlation with popularity is meaningful yet the correlations are present for about 10% of samples for BArea_pSTVLen variable and for 30% for the Motor_transit variable. Permeability showing a negative correlation is contrary to expectation. Once again, we found no reliable relationship between walking behavior and the combined popularity variable through the regression analysis results presented here.

Based on these findings, we see that certain morphological and streetscape attributes we measure do have a certain level of impact on the popularity of streets based on social media posts and number of people detectable on street view imagery. Some of these are expected and some align with our findings in literature; i.e. it is expected for Google Place frequencies to have a high impact on the frequency of Instagram posts as these are already collected using Google Place location tags and it is not a surprise for WAV_Integration400 to affect the outcome variables – however, positively- as we expect to see more people on better connected streets based on literature.

Table 6.7 : Variable importance for the combined variable.

Variable	Importance
Gplaces_pSTVLen	**100.00**
Commercial	66.01
STVs_Width	36.77
Permeability	16.68
BArea_pSTVLen	13.40
Motor_transit	9.33

Table 6.8 : Variable coefficients for the combined variable.

(Intercept)	**0.25530613**
h(Commercial-1.49707)	0.11611406
h(1.49707-Commercial)	-0.03075453
h(1.57707-Gplaces_pSTVLen)	-0.06117286
h(STVs_Width-1.86313)	0.33464116
h(Permeability- -0.923842)	-0.02453103
h(Motor_transit-0.184969)	-0.02566126
h(BArea_pSTVLen-1.22334)	-0.05054471

Also as expected, Commercial activity attracts people and elements of Motor_transit negatively affect the walking experience. Some unexpected findings as was also found inconsistent in our neighborhood comparisons are Permeability, Green and Pavements to be negatively impacting popularity; and contrary to expectation, STVs_Width to have a positive impact and STVs_Height to have a negative impact on street activity. These contradict expectations due to the way they both impact enclosure and STVs_Height indicating higher density which is a positive influence on walkability.

Interpreting these results, we are able to compare the significance of some attributes on influencing streets' popularity but we cannot use these popularity variables to represent walkability and these regression models to predict walkability levels due to the inconsistencies we described above.

In the next section, to better understand the behavior of our attributes and their relationship with walkability, we use the unsupervised learning method of k-means and identify some street typologies. To infer some conclusions, we compare the known walkability related qualities of these clusters with their attribute value ranges.

6.2 Classification of STVs Based on Indicator Values

To classify STVs, a selected set of 22 indicator values of all 585 street space samples were used, and the “R” software’s clustering algorithm based on the Hartigan and Wong (1979) method was utilized to generate 5, 6, 7 and 8 number of clusters. Five number summaries were explored through boxplots for comparing the clusters’ attribute values (Figures 6.1, 6.4-6.8, 6.11-6.17, 6.20-6.35, 6.38-6.50, 6.55-6.58). For legibility purposes, outlier STVs that were 5 times the interquartile range (IQR) smaller or larger than the upper limits of 1st and 3rd quartiles were removed from the set for all indicators for the analysis while making the boxplots, even though the clusters include all STVs as also seen in the cluster maps (Figures 6.3, 6.19, 6.37, 6.52, 6.54).

The selection of the 22 indicators was done through an elimination process. Firstly, attributes that were represented by other attributes and that were not considered independently distinctive were omitted: STVs_Perimeter, STVs_Volume, WAV_FacadeWidth, WAV_FacadeHeight, BArea_pSTVArea, BArea_pSTVLen, FArea_pSTVArea, AV_FArea, STVs_Enclosure and Commercial were considered to be so. Then, those that did not show significant differences between the median and range values between neighborhoods considered walkable (Caferağa and Chiado) and not walkable (Ajuda and Hasanpaşa) were omitted, which were: FlowLengthTSTVArea, WAV_FlowIncline, STVs_ElevationChange, Cov_CSElevation, Cov_CSDiameter, Cov_NFloors, Cov_BArea, Cov_FArea, Cov_CSCompactness, Cov_CSSquareness and Permeability. STVs_NFacadesPerM, AV_BArea, WAV_FacadeHeightTWidth, WAV_FacadeArea, WAV_CS_Compactness and WAV_CS_Squareness were not omitted even thought they were not significantly different among walkable/not walkable neighborhoods because they were considered to represent issues not otherwise represented in the dataset and were theoretically interesting. Green indicator was kept for showing high impact in the predictive model even though it was negatively correlated to popularity and also showed negative relationship with walkable/non-walkable neighborhoods.

Cov_CSSkyview was omitted due to being very indirectly perceivable as a diversity indicator. Among the Space Syntax indicators, WAV_Integration400 was the only one retained in the set since all these indicators represented 2d street network connectedness and if included, would over represent this characteristic within the clusters. Also, among Space Syntax indicators, Integration has been found to have a strong explanatory power for walking behavior (Özbil et al., 2015). Final set of attributes are listed in Table 6.9.

Among the STV clustering of 5, 6, 7 and 8, the most meaningful in terms of distinguishing the street types was the group of 6 clusters, the maps of which are presented in Figures 6.3, 6.10, 6.19, 6.37, 6.52 and 6.54. If we look at this classification of streets closely, we see that some clusters are concentrated in one neighborhood and some do not exist at all in some neighborhoods. For example, cluster 4 only exists in Chiado, and at a first glance, seems to represent the larger and more square-like spaces as well as those that connect to them. Or, Ajuda seems to consist mainly of three types of street spaces which belong to clusters 1, 5 and 6. This is similar to Caferağa and Hasanpaşa, even though the frequencies of STV classes differ.

Here we explore each cluster and a set of their representative streets, with the purpose of identifying street space types and their distinguishing characteristics based on their built environment attributes. Then we assess their walkability-related qualities that we suggest improvement scenarios for in the following chapter. If we compare the combined popularity variable between these clusters of STVs, we see that Cluster 2 that almost exclusively appear in Chiado has the highest median value and cluster 6 that make up a large part of Ajuda and Hasanpaşa has the lowest (Figure 6.1). It should be noted that even though we take a look at the combined popularity variable values for the Clusters of STVs, we do not accept this value as a proxy for walkability, since we have determined that based on the data collected within the scope of this study, this value does not consistently correlate with many of the widely accepted walkability related built environment attributes and so cannot be said to represent this quality. Instead, we see them as an additional factor in understanding the nature of the clusters. Using the boxplots, we look at attributes that show significant differences among clusters; the known qualities and the walking experience offered by the streets that fall into each cluster and draw out their unique characteristics.

We then propose that different types of streets should be evaluated differently rather than be judged using the same walkability assessment criteria. Based on our study of clusters, we propose that streets should first be grouped based on the values of certain indicators and suggest a set of attributes to use in evaluating each group. The reasoning behind the development of this method is explained through the findings regarding the behavior of attributes under the cluster summaries and a guideline for this grouping-based assessment method as well as improvement scenarios for each type of street is presented in the following chapter.

Table 6.9 : Selected attributes and their characteristic groups.

Characteristic		Attribute
Density		
	Physical	**FArea_p_STVLen**
	Use	**GPlaces_pSTVLen**
Diversity		
	Morphological	**STVs_#FacadesPerM**
	Land use	**GPlaces_pSTVLen**
Connectedness		
	Space Syntax	**WAv_Integration400**
(Human) Scale		
		STVs_Area
		STVs_Length
		STVs_Width
		STVs_Height
		STVs_#FacadesPerM
		WAV_FacadeArea
		AV_Floors
		AV_BArea
Complexity		
	Granularity/Articulation	**STVs_#FacadesPerM**
		WAV_FacadeArea
		STVs_PerimTArea
	Other streetscape features	**Green**
		Motor_transit
	commercial amenities	**GPlaces_pSTVLen**
Enclosure		
		STVs_Height
		STVs_HeightTWidth
		WAV_FacadeHeightTWidth
		WAV_CS_Skyview
Shape		
		STVs_Compactness
		WAV_CS_Compactness
		WAV_CS_Squareness
		STVs_PerimTArea
Permeability/Transparency		
		GPlaces_pSTVLen
Infrastructure Quality (and Maintenance)		
		Green
		Pavement
		Motor_transit
		Negative

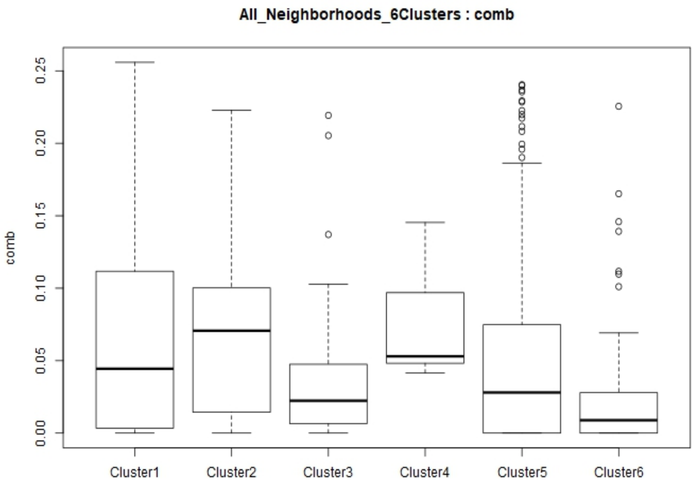
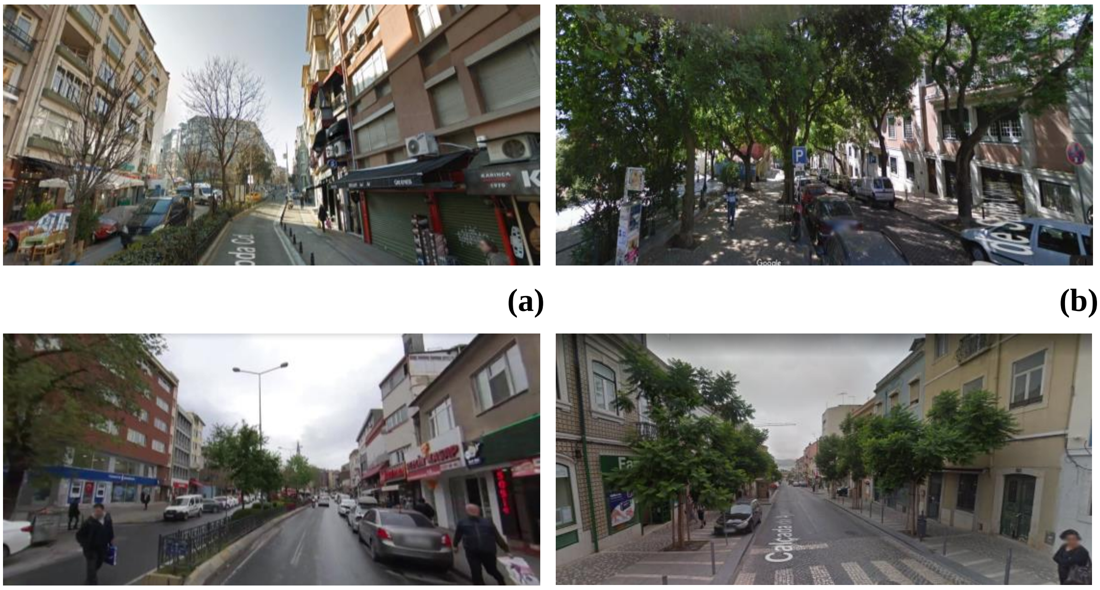


Figure 6.1 : Combined Popularity Variable values for all clusters.

Cluster summaries explain how indicators behave compared to expectations based on the hypothesis of this research and walkability literature. A more conclusive revision of the indicators is presented at the end of the cluster summaries. Sample images (Figures 6.2, 6.9, 6.18, 6.36, 6.51, 6.53) captured from Google Street View are provided for STVs belonging to each cluster.

Cluster 1



(a) (b) (c) (d)

Figure 6.2 : Cluster 1 images: (a) Caferaga, (b) Chiado, (c)Hasanpasa, (d) Ajuda.

Among the street spaces that fall in cluster 1 (Figures 6.3), some relatively well known, popular (Figure 6.1) and wide streets (Figure 6.4) are represented. Most notable of these are: Moda Caddesi from Caferağa, a part of Kurbağalıdere Caddesi from

Hasanpaşa, Rue de Santa Catarina along with the square like space north of Miradouro (view terrace) da Santa Caterina from Chiado and Calçada da Ajuda from Ajuda. This is an interesting finding, as it means that this cluster is able to identify the main streets of every neighborhood's studied areas except for Chiado. In the case of Chiado, the streets around the Miradouro falling within this cluster are also very well-known and popular with both the locals and the tourists. Even though the median value of the combined popularity variable for this cluster is not the highest (Figure 6.1), its IQR's upper limit and max value are the highest, and the STV representing the street space behind the Miradouro has one of the highest combined popularity variable value within the ranges of this value among all clusters.

Most of the STV attributes measured for this cluster show unexpected trends considering the popularity of these main streets among its STVs, even though we should keep in mind that these main streets are not the only ones in the cluster.

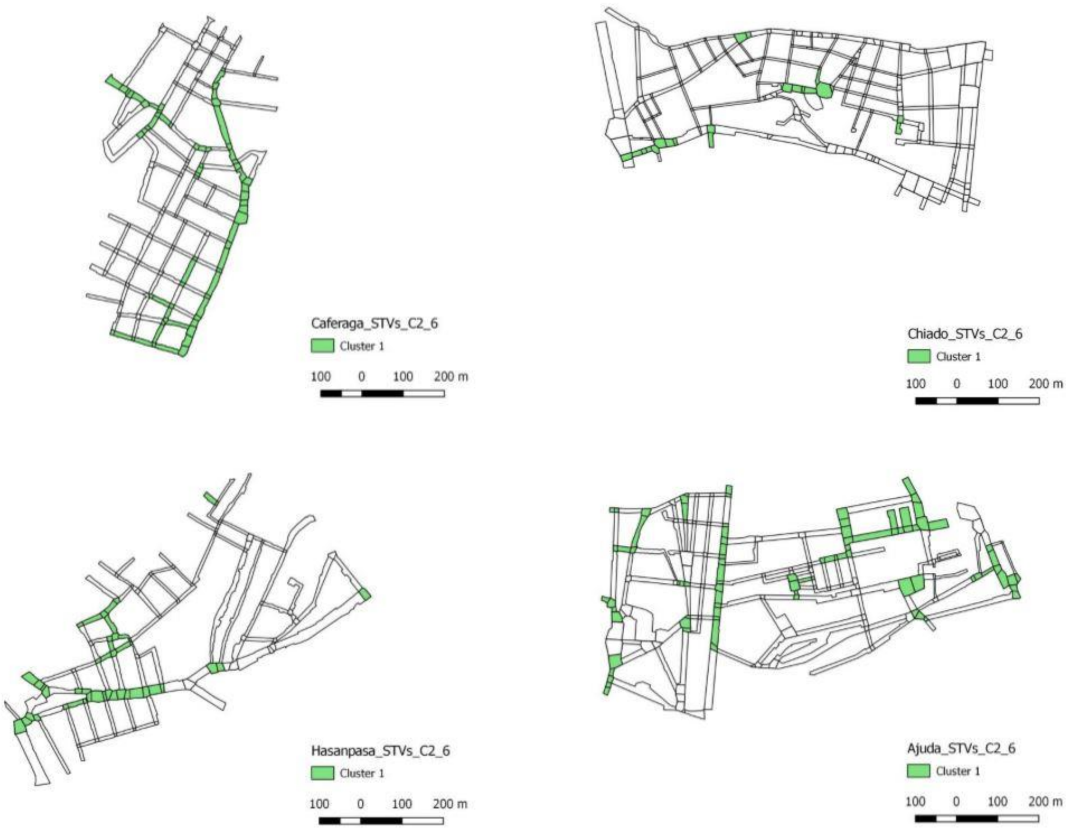


Figure 6.3 : Cluster 1 maps of Caferaga, Chiado, Hasanpasa and Ajuda.

The most significantly different attribute compared to other clusters is the Motor_transit (Figure 6.4), telling us that cars and other motor vehicles have been sighted in Google Street View images within this cluster more than in any other.

Permeability, also measured based on Google Street View images, indicates that not as many doors and windows have been sighted on these streets as most of the others (Figure 6.6). Both these indicators imply lower walkability for streets based on literature contrary to the observed and well-known attractiveness of these streets. An abundance of motor vehicles on a street never enhances walkability, thus, this cluster of streets can be said to be popular and active despite the fact that there are cars everywhere. Permeability on the other hand, has been proven to support safety and walkability in many studies. The low level of this indicator measured (Figure 6.6) for these rather commercially active and popular streets point to the issue of windows and doors not being easily identified on glass shop window facades. So even though these streets are highly permeable with several shops and restaurants taking up their ground floor level facades, they measure low. Based on this we can say that this indicator is effective for measuring residential streets, but not mixed use or commercial ones.

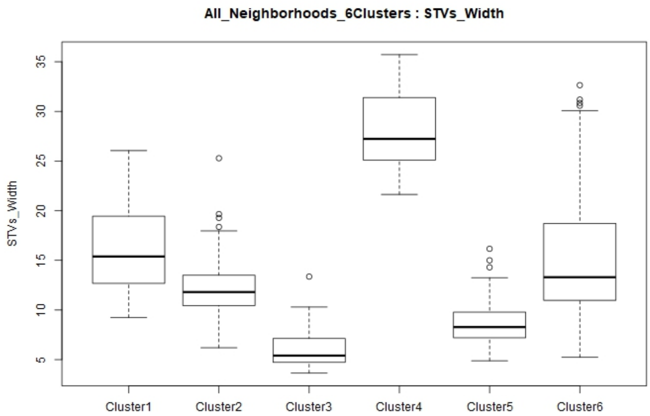


Figure 6.4 : STV Width values for all clusters.

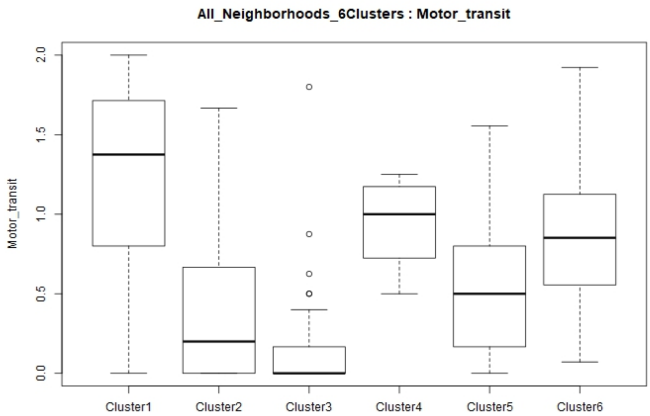


Figure 6.5 : Motor Transit values for all clusters.

Two indicators that show expected trends for these relatively popular streets are the façade widths (Figure 6.7) with lower values and Commerce (Figure 6.8), showing a higher upper limit and max value than any other cluster. While narrow facades are expected to bring on the potential for a greater number of buildings and therefore a rich variety of functions and a frequently changing, attractive street wall; looking at this cluster, we could conclude that the Commerce indicator measuring the number of shops, commercial and other business activities based on street view images was more indicative of functional diversity and even walking preference then most other morphological qualities. However, the following clusters reveal that GPlaces_pSTVLen (Figure 6.11) indicator is a more reliable measure of commercial activity then the Commerce indicator.

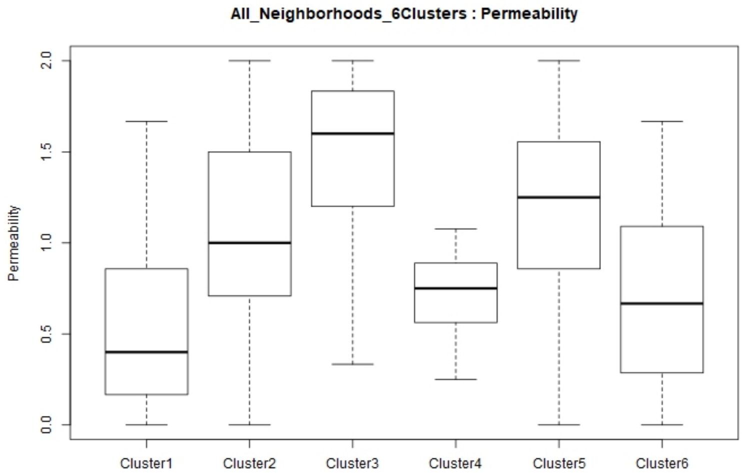


Figure 6.6 : Permeability values for all clusters.

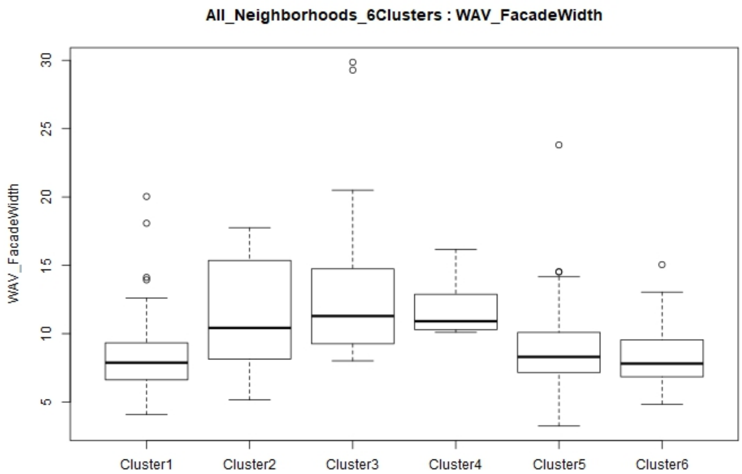


Figure 6.7 : Weighted Average of Façade Width values for all clusters.

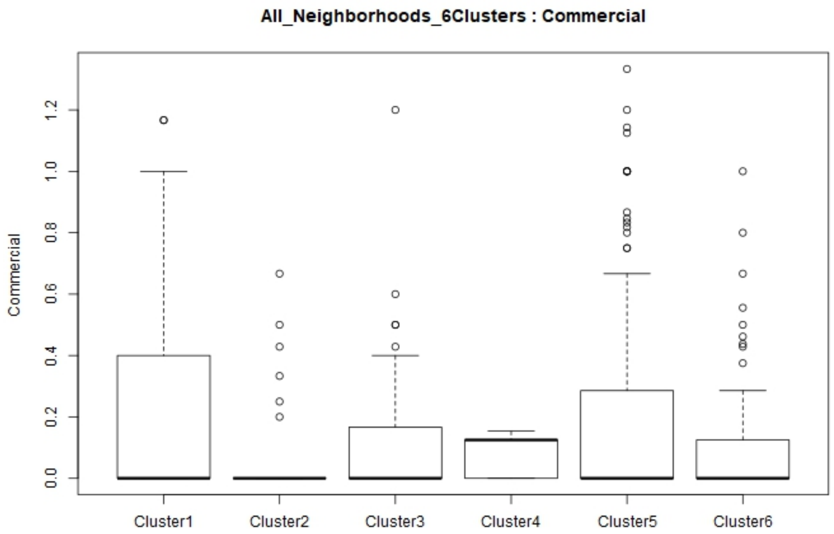


Figure 6.8 : Commerce indicator values for all clusters.

Cluster 2

Figure 6.9 : Cluster 2 image from Chiado

This cluster almost exclusively represents some of the most commercially active (Figure 6.11), popular and attractive streets in Chiado. These are relatively wide streets (Figure 6.4) with a high level of built area density (Figure 6.12) and mostly two lane, two-way car traffic. The cluster has the highest median value for combined popularity variable along with some density and Space Syntax indicators (Figure 6.1, Figures 6.8-6.9, 6.12-6.13). Highest median values for BArea and FArea per street length as well as highest range upper limits for AV_BArea and AV_FArea point to high densities and indicate buildings with larger footprints and greater number of floors than other street spaces (Figures 6.14-6.15).

Large BAreas do indicate a possibility of large facades therefore less variety of functions and dull street faces but not only are the façade areas and widths not the largest within the clusters, streets in this cluster also have reputations indicating this is not the case at all. Part of Calçada do Combro and the south parts of Rua de Alecrim, Rua das Flores, Rua de Sao Paolo and Travessa do Alecrim which fall within this cluster are known to have some of the most active street lives in Lisbon; they are highly popular and attractive for both tourists and the locals, and are well connected with similarly active streets to neighborhoods like Bairo Alto, Baixa and Cais de Sodre which are within walking distance.

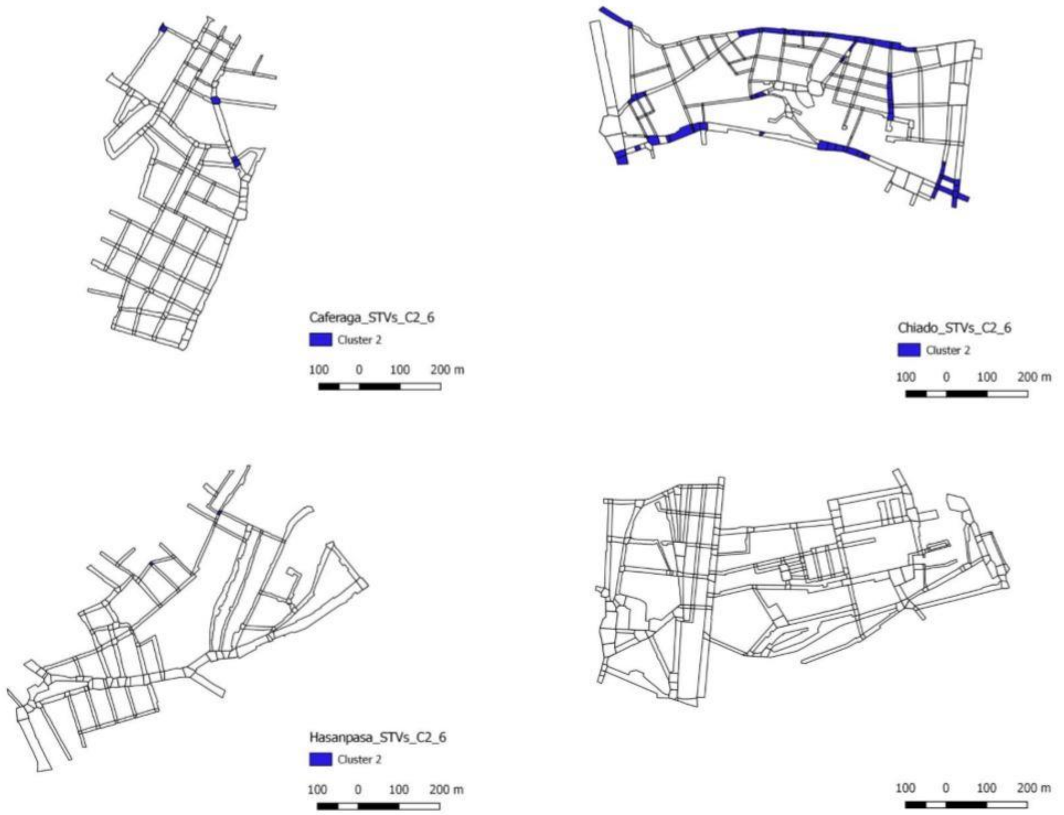


Figure 6.10 : Cluster 2 maps of Caferaga, Chiado, Hasanpasa and Ajuda.

Along with cluster 1, the streets in this cluster have the highest median values for the Space Syntax indicator WAV_Choice400, pavement and STVs_Compactness (Figures 6.16, 6.20, 6.21). Expectedly it has the highest range upper limit and max values for WAV_Integration400 (Figure 6.17) and GPlaces_pSTVLen (Figure 6.11). The lowest median and/or range limits this cluster has are for STVs_Perimeter, STVs_Length, STVs_ElevChange and Negative (Figures 6.22-6.15). This indicates block sizes remaining in the lower range of the studied sample that is linked with higher walkability, less inclination, which is rare to find in the neighborhood of Chiado but makes life easier for pedestrians, and fewer instances where “abandoned”, “calamity” or “demolished” were identified in street view images. The fact that the Commercial variable shows lower ranges for this cluster point to an inaccuracy in the method, GPlaces_pSTVLen variable should be used to measure this attribute.

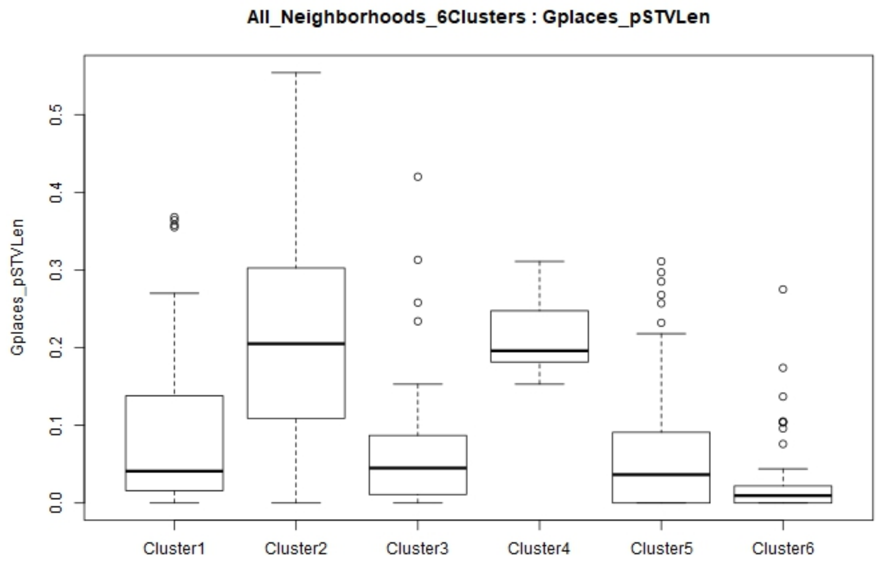


Figure 6.11 : Google Places per STV Length indicator values for all clusters.

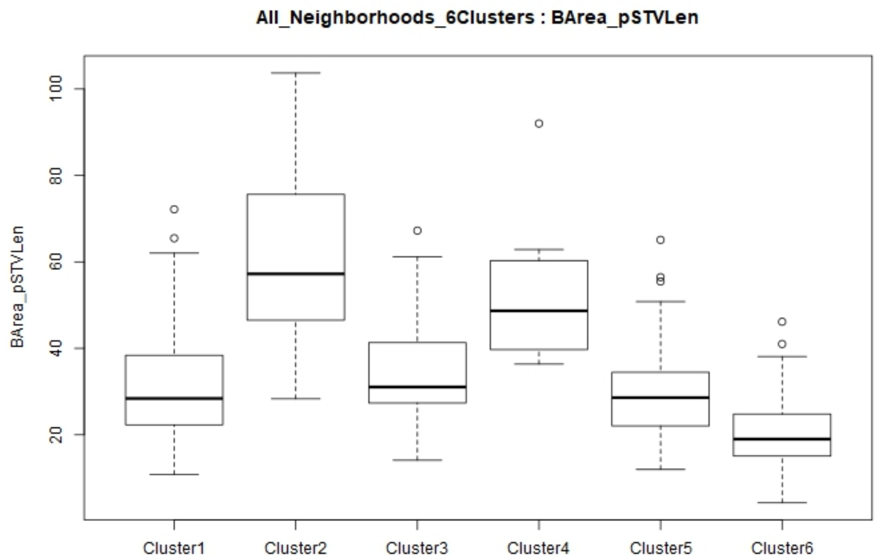


Figure 6.12 : Building Area per STV Length indicator values for all clusters.

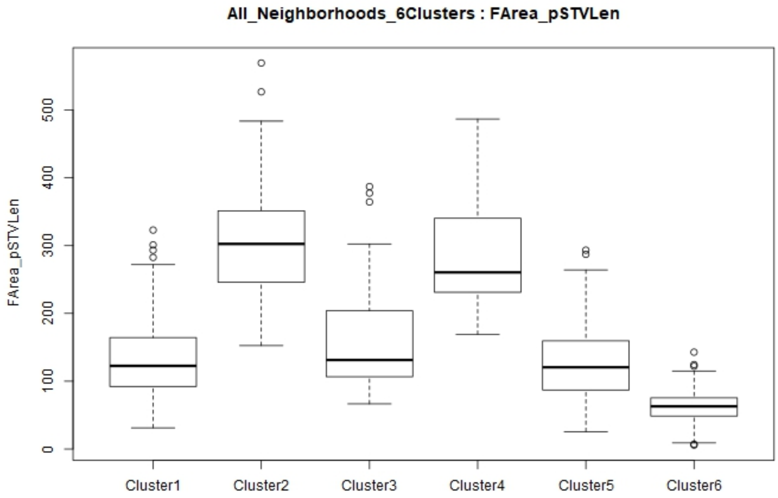


Figure 6.13 : Floor Area per STV Length values for all clusters.

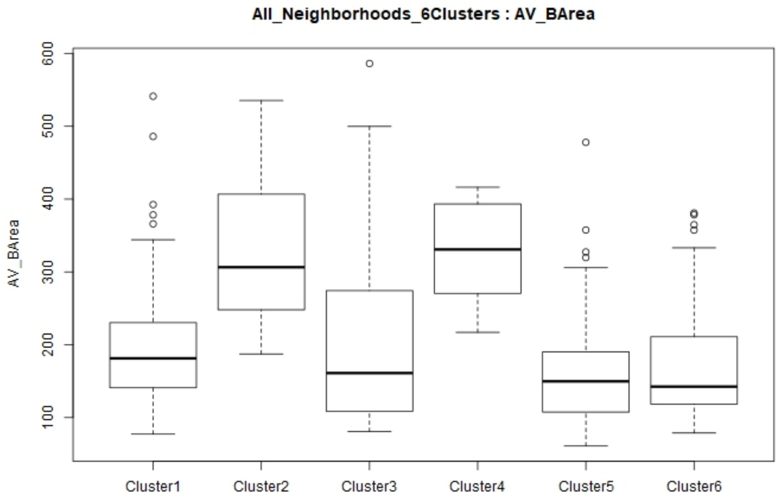


Figure 6.14 : Average Building Area values for all clusters.

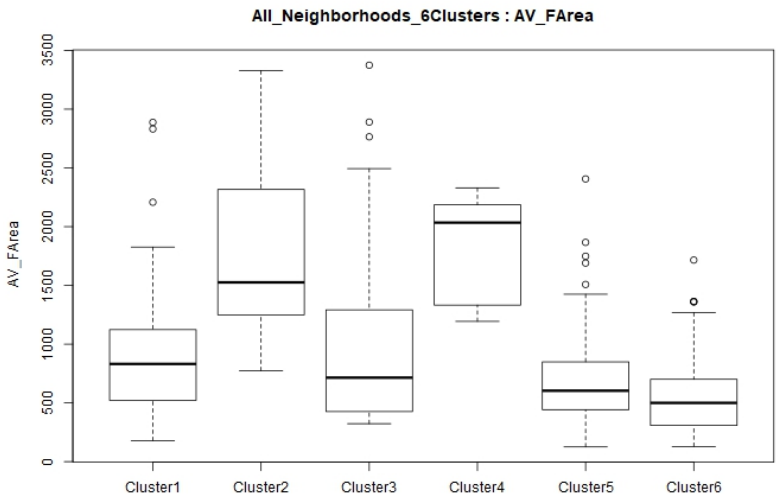


Figure 6.15 : Average Floor Area values for all clusters.

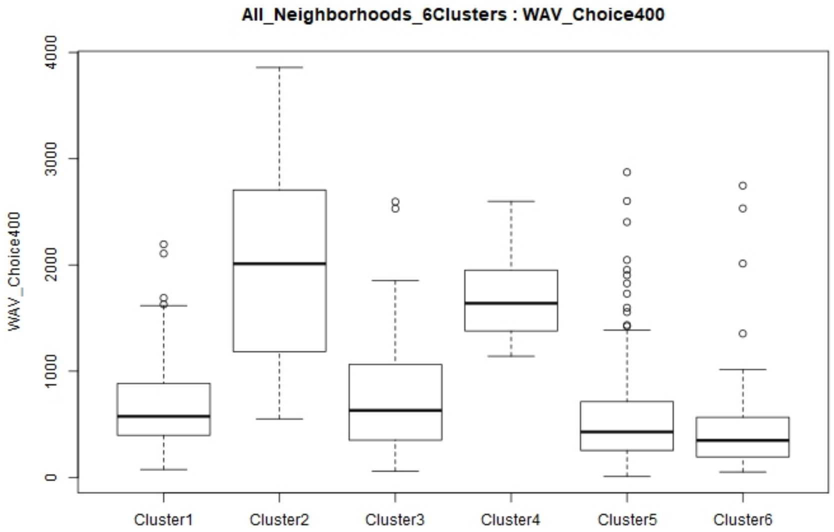


Figure 6.16 : Weighted Average of Choice (r: 400m) values for all clusters.

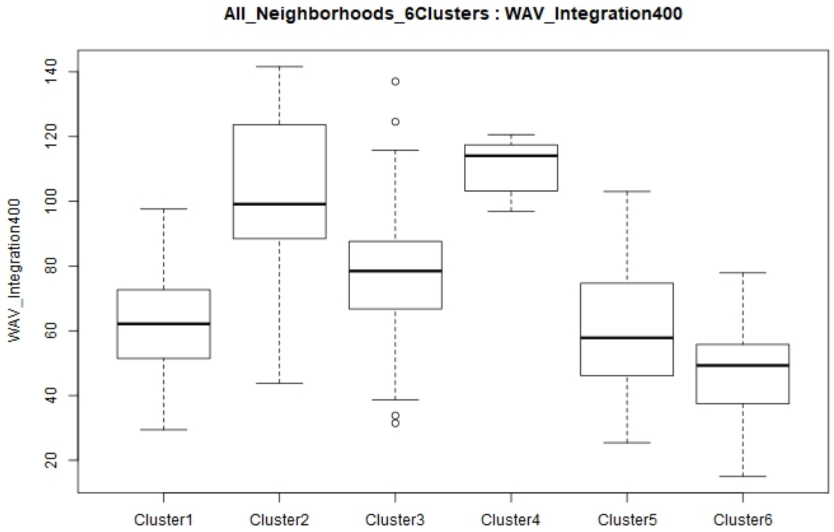


Figure 6.17 : Weighted Average of Integration (r: 400 m) values for all clusters.

Cluster 3

(a) **(b)**

Figure 6.18 : Cluster 3 images from (a) Hasanpasa and (b) Chiado.

Also almost exclusively representing streets in Chiado, this cluster has indicator values that most strongly agree with the hypothesized ranges for high levels of walkability. A majority of the streets that fall into this cluster are very popular, commercial, relatively narrow, generally well enclosed, have a high built area density and a single lane traffic.

Permeability (Figure 6.6), BArea_pSTVLen (Figure 6.8), BN_pSTVLen, STV_HeightTWidth, STV_Enclosure, FlowLength_TSTVArea, STV_PerimTArea (Figures 6.26-6.30), all show highest median values and STVs_Area, STVs_Volume, WAV_CS_Skyview, WAV_Connectivity (Figures 6.31-6.34) and Motor_transit (Figure 6.5) have the lowest median values aligned with hypothesized characteristics that support walkability of streets. A majority of its streets are residential, even though some parts of the commercially very active streets Rua de Alecrim and Rua das Flores fall within this cluster.

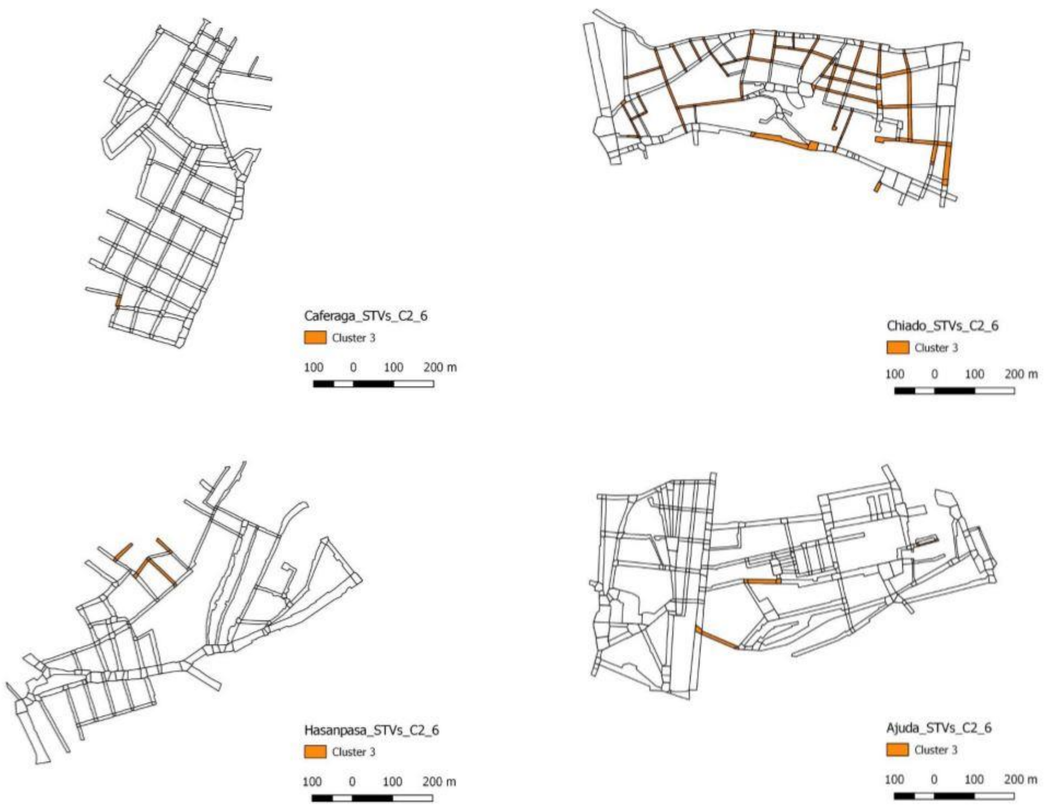


Figure 6.19 : Cluster 3 maps of Caferaga, Chiado, Hasanpasa and Ajuda.

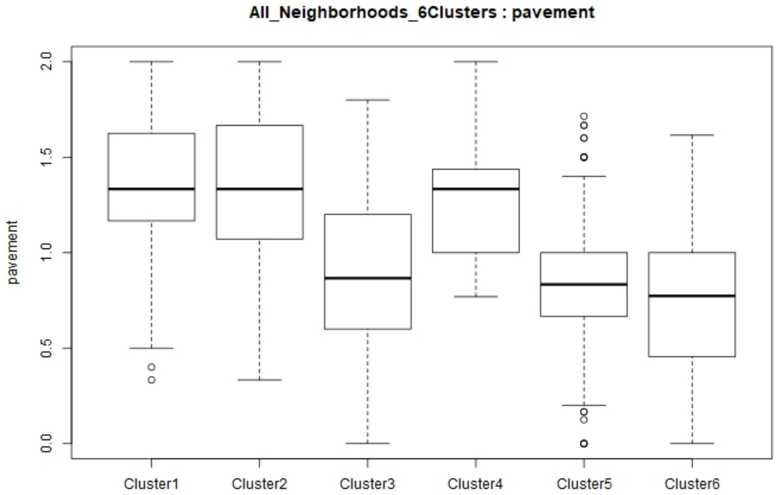


Figure 6.20 : Pavement indicator values for all clusters.

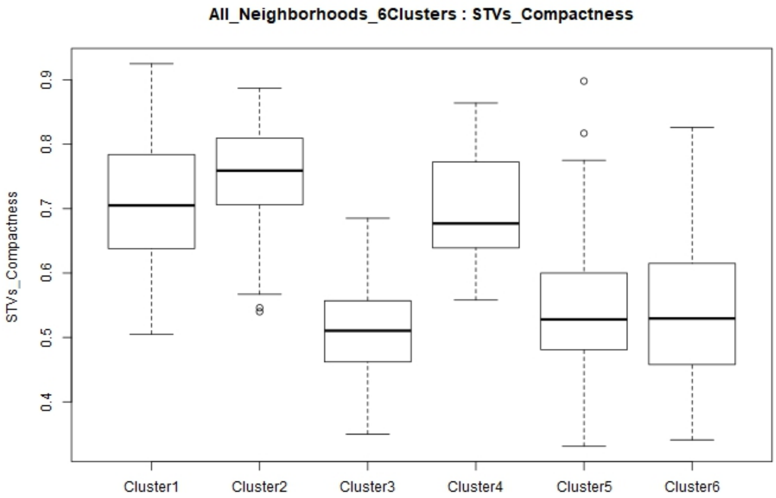


Figure 6.21 : STV Compactness values for all clusters.

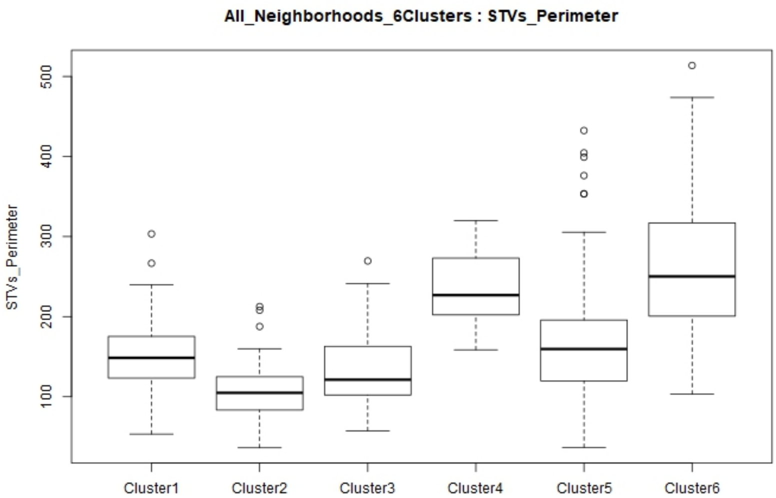


Figure 6.22 : STV Perimeter values for all clusters.

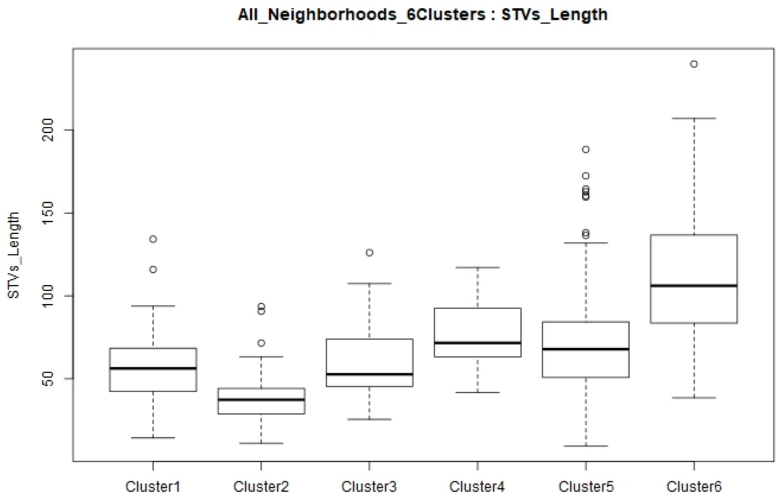


Figure 6.23 : STV Length values for all clusters.

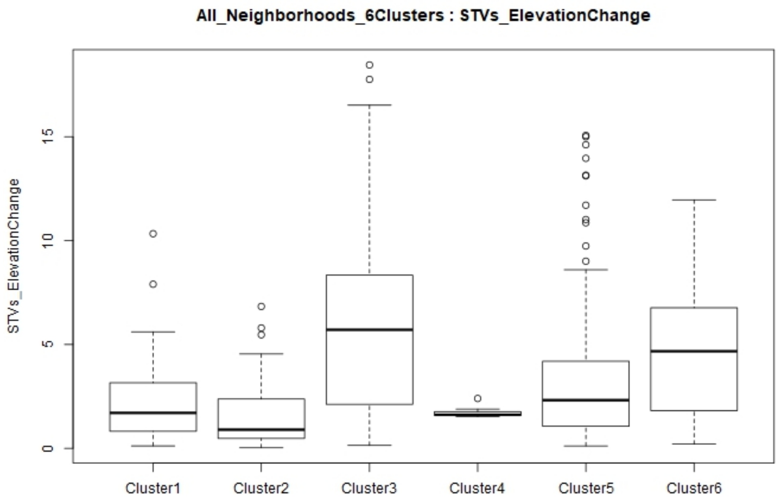


Figure 6.24 : Elevation Change values for all clusters.

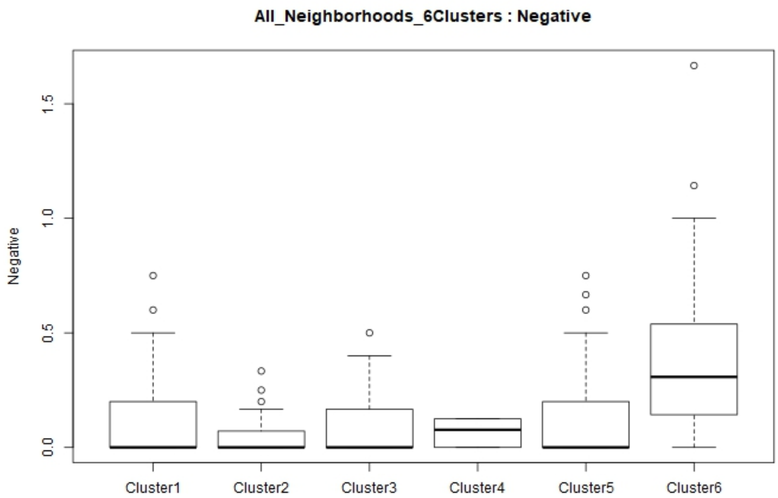


Figure 6.25 : “Negative” indicator values for all clusters.

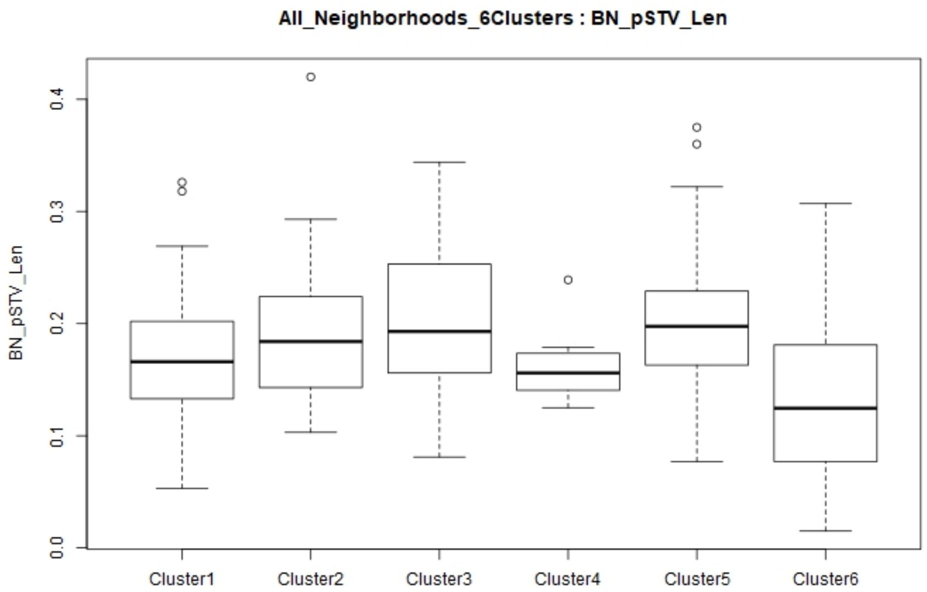


Figure 6.26 : Number of Buildings per STV Length values for all clusters.

The combined popularity variable value is relatively low (Figure 6.1), probably due to the streets being more generic as they consist of similar, mainly residential buildings, and so being less photogenic or "instagrammable". STVs_Compactness and WAV_CS_Squareness (Figure 6.21, 6.35) which account for how square-like a street space is, have the lowest median values for this cluster among all clusters which is expected considering the thin and long shapes of streets that fall within this cluster.

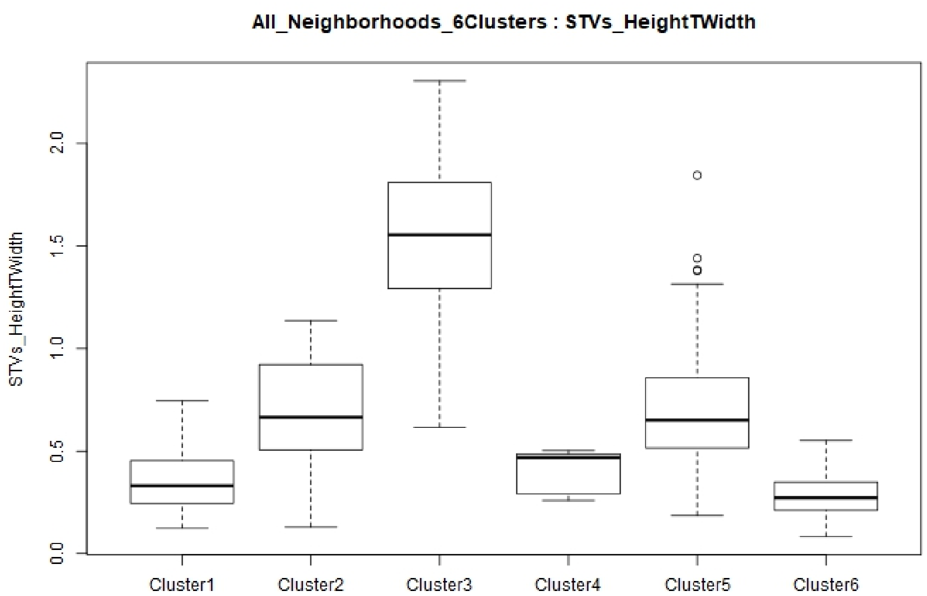


Figure 6.27 : STV Height to Width values for all clusters.

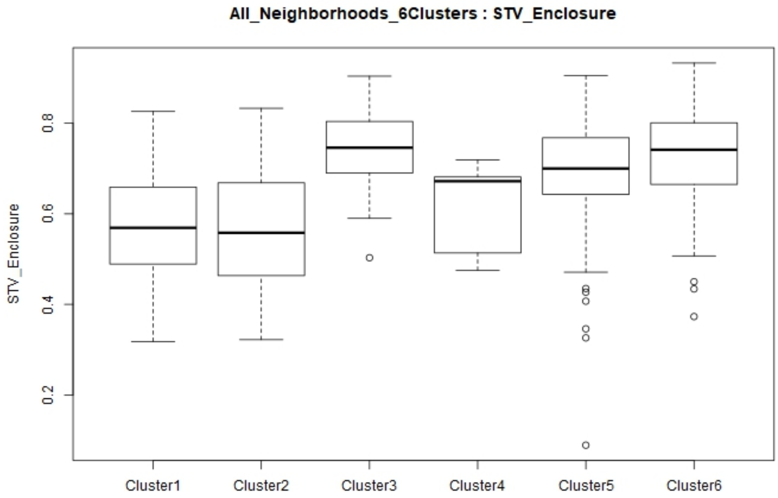


Figure 6.28 : STV Enclosure values for all clusters.

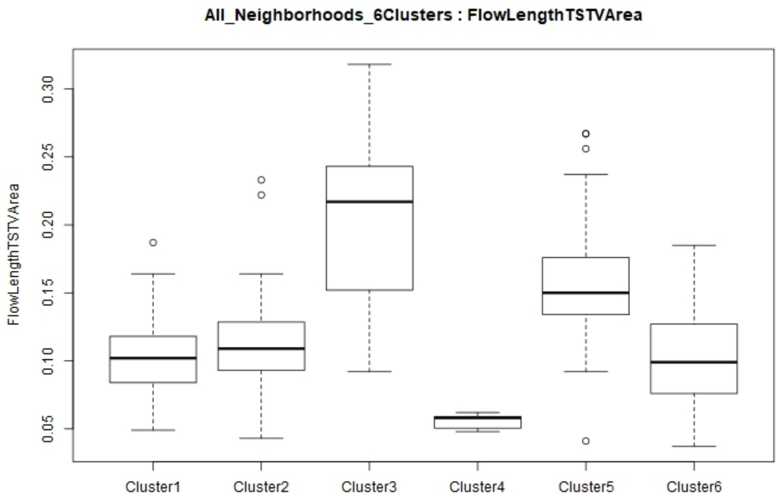


Figure 6.29 : Flow Length to STV Area values for all clusters.

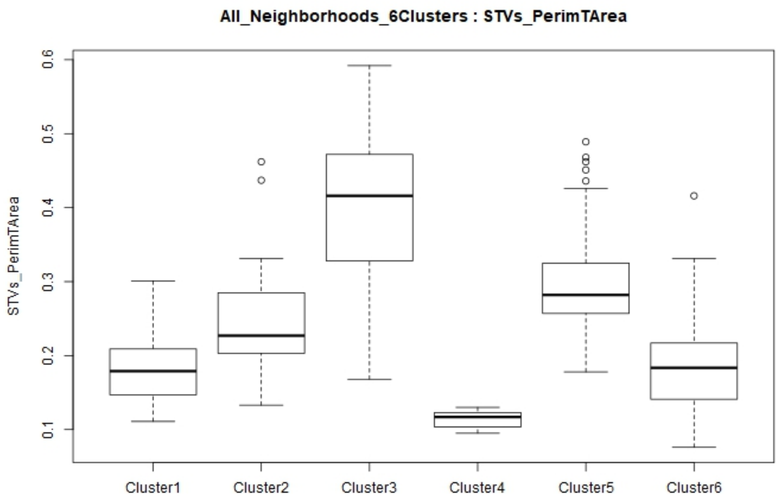


Figure 6.30 : STV Perimeter to Area values for all clusters.

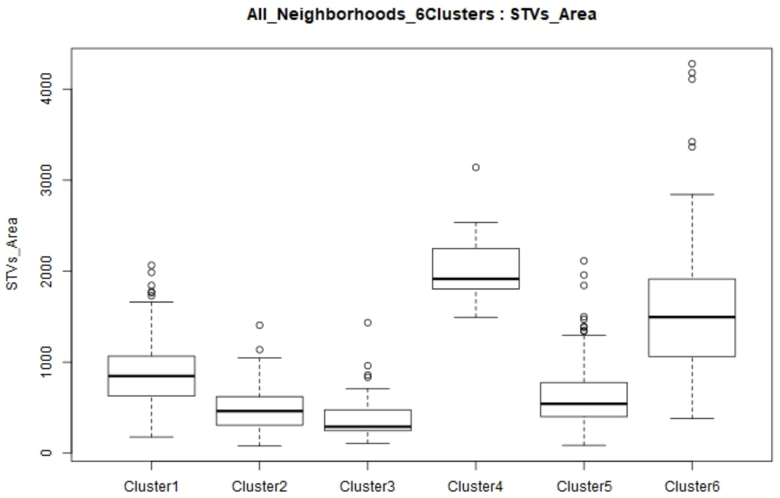


Figure 6.31 : STV Area values for all clusters.

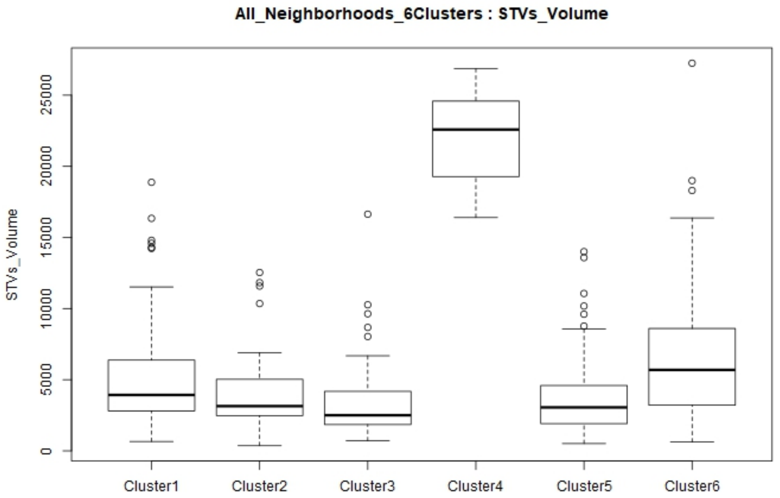


Figure 6.32 : STV Volume values for all clusters.

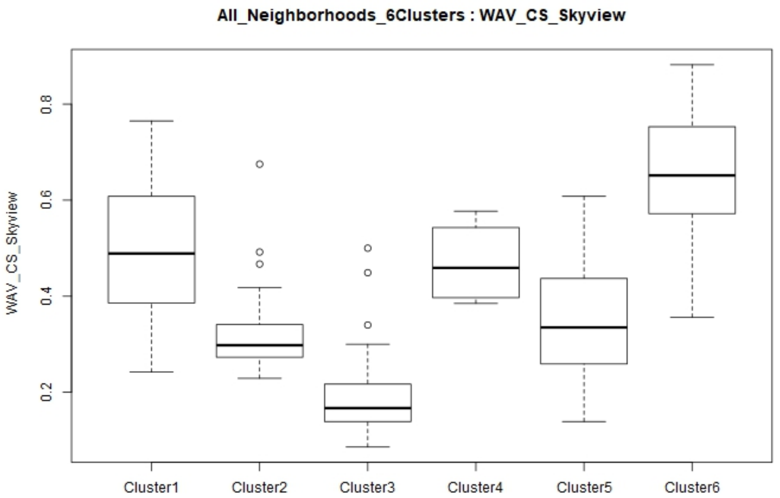


Figure 6.33 : Weighted Average of CS Skyview values for all clusters.

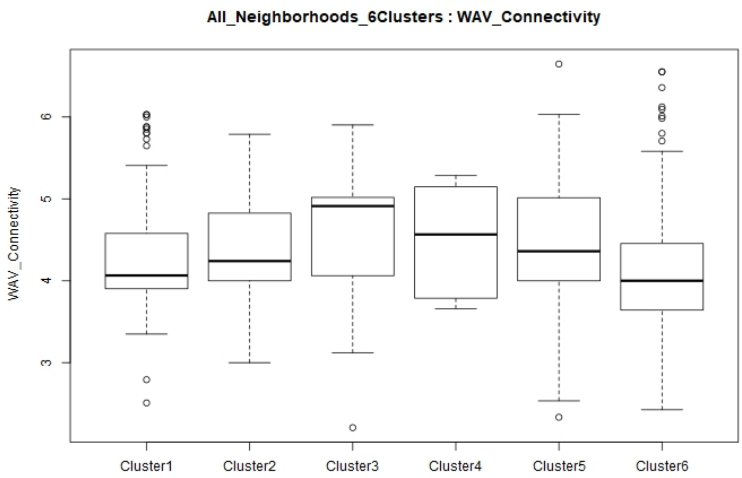


Figure 6.34 : Weighted Average of Connectivity values for all clusters.

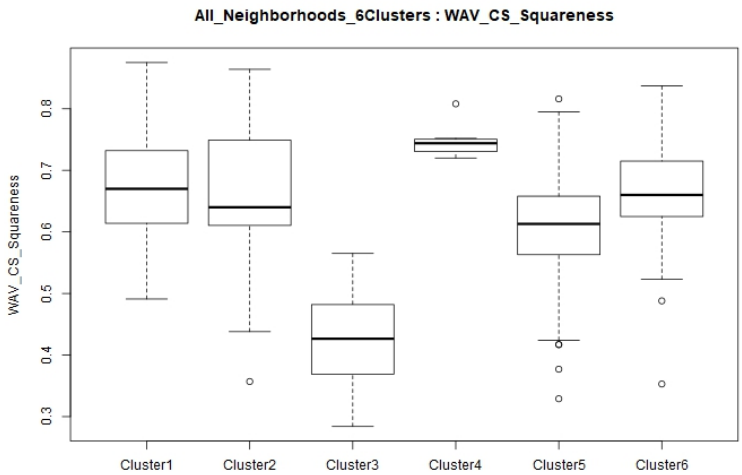


Figure 6.35 : Weighted Average of CS Squareness values for all clusters.

Cluster 4

Figure 6.36 : Cluster 4 images from Chiado.

This cluster exclusively represents a set of squares, a boulevard and their connected street spaces in Chiado. These include the two central and very popular public plazas: Praça Luis de Camoes and Praça de Sao Paulo, two smaller squares: Largo Barao Quintela and the square at the intersection of Avenida Dom Carlos and Rua da

Esperanca, as well as chunks of very prominent streets of Chiado that connect to them: Rua do Alecrim, Rua das Flores, Rua da Boa Vista and Avenida Dom Carlos. The combined popularity variable median value belonging to this cluster is the second highest among the studied clusters (Figure 6.1). Notably containing some of the most popular and renown public spaces in the city of Lisbon, the value ranges of this cluster's attributes are informative to understand the behavior of a number of characteristics of rather central, imageable, popular and thus quite walkable street spaces. Quite expectedly, a number of Space Syntax attributes (WAV_Integration400, WAV_Connectivity, WAV_TotalDepth400, WAV_NodeCount400,) (Figures 6.17, 6.34, 6.38, 6.39); Enclosure attributes (STVs_Height, AV_Floors, WAV_FacadeHeight) (Figures 6.40-6.42 as well as the Diversity attributes measured by the coefficient of variations for building size (Cov_BArea, Cov_FArea, Cov_NFloors) (Figures 6.43-6.45) and morphological attributes (Cov_CSSkyview, Cov_CSCompactness, Cov_CSDiamater) (Figures 6.46-6.48) have the highest median values in this cluster. Contrary to expectation based on literature promoting smaller-scale built environment features to improve walkability, AV_BArea, AV_FArea, STVs_Area and STVs_Volume (Figures 6.14, 6.15, 6.31, 6.32) show the highest median values in this cluster. As a revealing outcome, the Inclination attributes of Cov_CSElevation and WAV_FlowIncline (Figures 6.49, 6.50) both show the highest median values for this cluster which tells us that the hilly street spaces can still be a considerably popular and arguably have a high level of walkability.

Figure 6.37: Cluster 4 map of Chiado.

One of the most notable findings of this study is based on the two Shape attributes of STVs_Compactness and WAV_CSSquareness (Figures 6.21, 6.35) which show the highest median values for this cluster. Calculated solely based on quantitatively measured morphological properties, these attributes reveal how likely a street space is to be a square; and this cluster is measured to consist of highly square-like spaces which are actually quite popular and active public plazas.

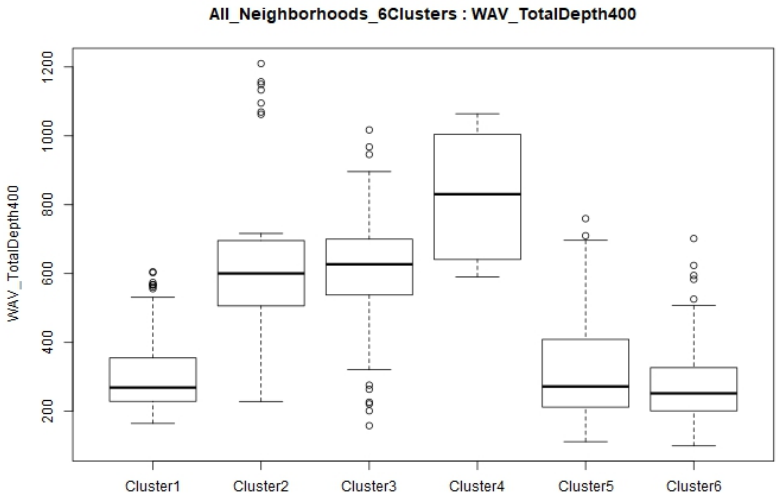


Figure 6.38 : Weighted Average of Total Depth (r: 400m) values for all clusters.

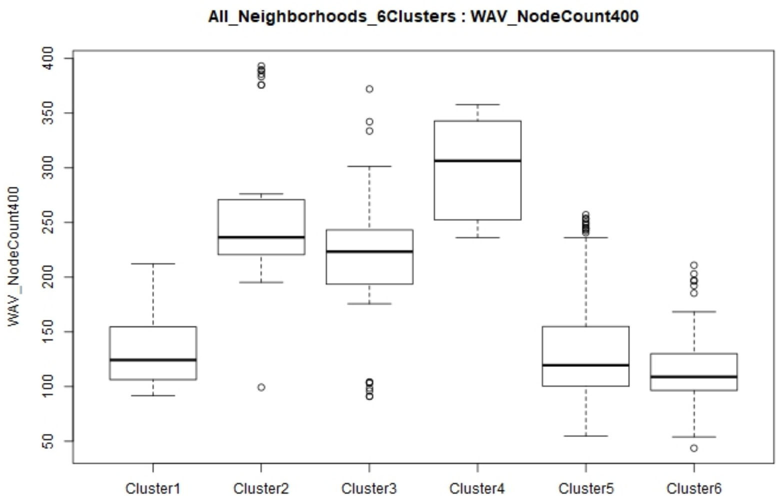


Figure 6.39 : Weighted Average of Node Count (r: 400m) values for all clusters.

This cluster shows some attribute behaviors contradicting the expectations similarly with clusters 1 and 2 based on walkability literature which commonly proposes walkability measuring methods to assess street-like spaces rather than square-like spaces, most likely due to the squares' unique morphological characteristics. We argue here that all open spaces in an urban neighborhood can be assessed by measuring quantitative morphological and streetscape properties; and to do this they should first be classified based on their characteristics and be evaluated with different criteria.

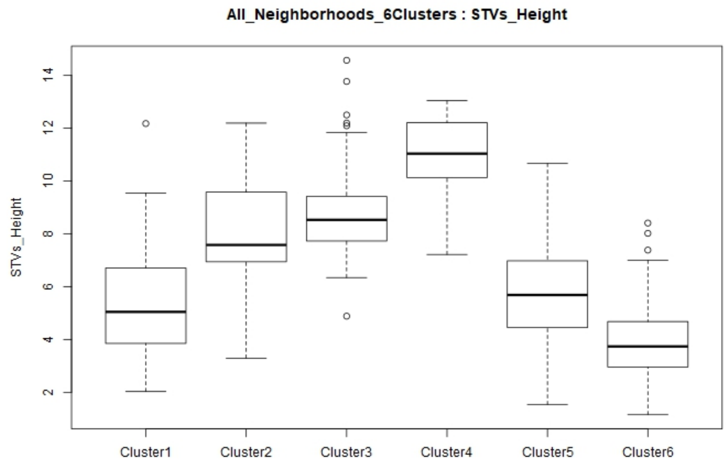


Figure 6.40 : STV Height values for all clusters.

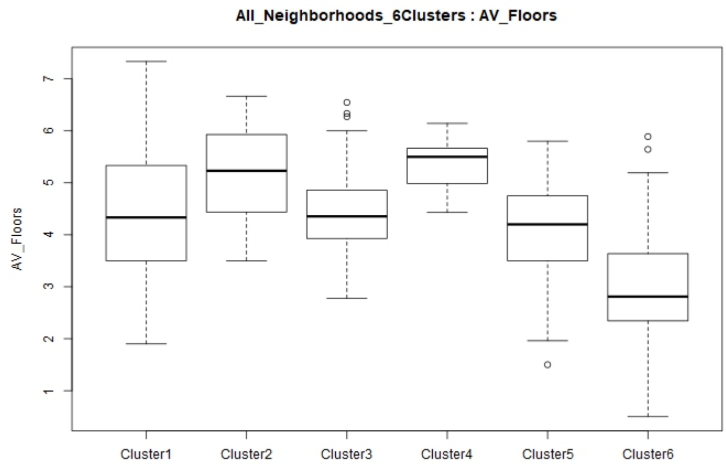


Figure 6.41 : Average Floors values for all clusters.

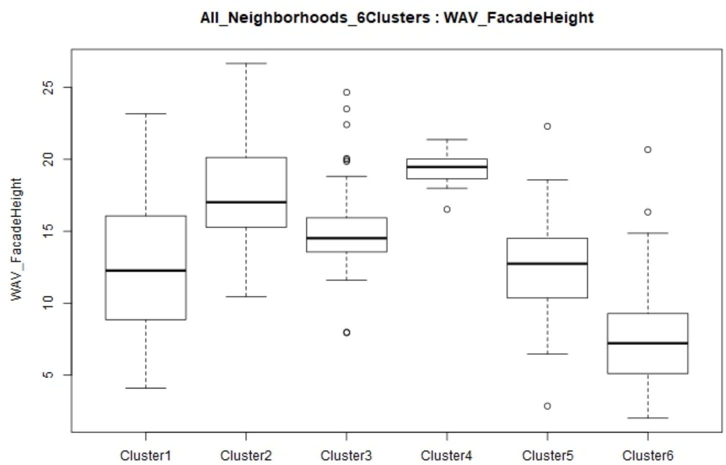


Figure 6.42 : Weighted Average of Façade Heights values for all clusters.

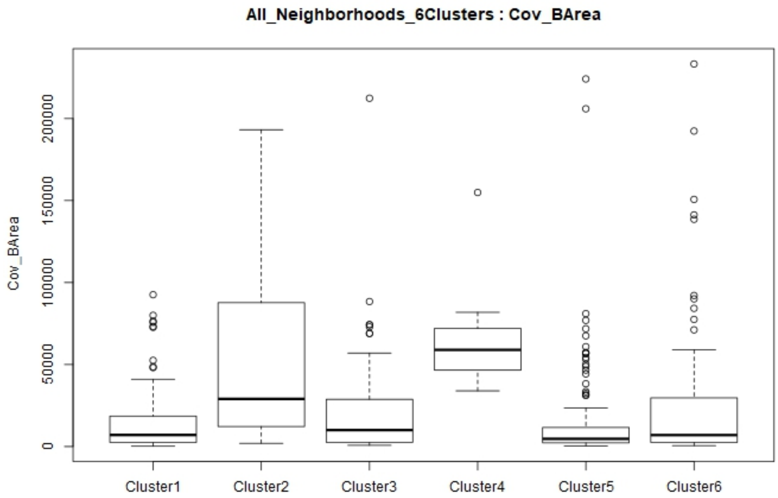


Figure 6.43 : Coefficient of Variation of Building Area values for all clusters.

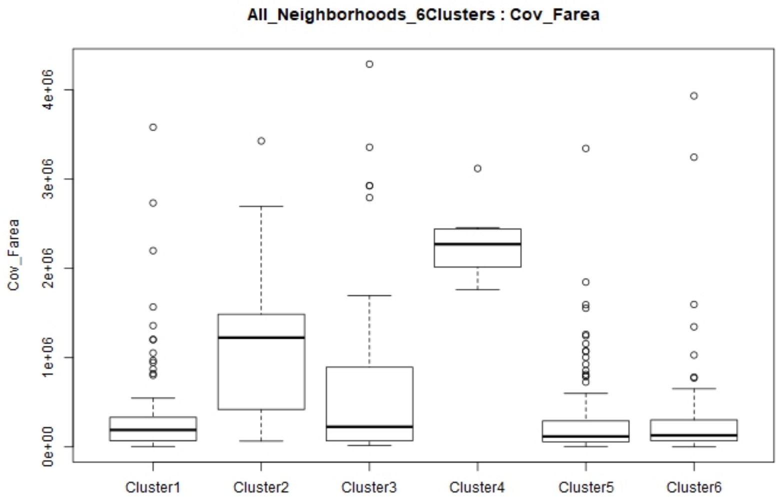


Figure 6.44 : Coefficient of Variation of Floor Areas values for all clusters.

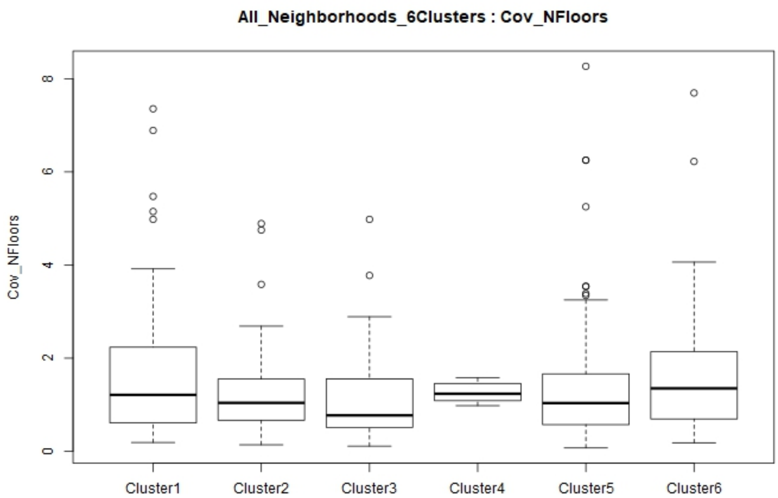


Figure 6.45 : Coefficient of Variation of Number of Floors values for all clusters.

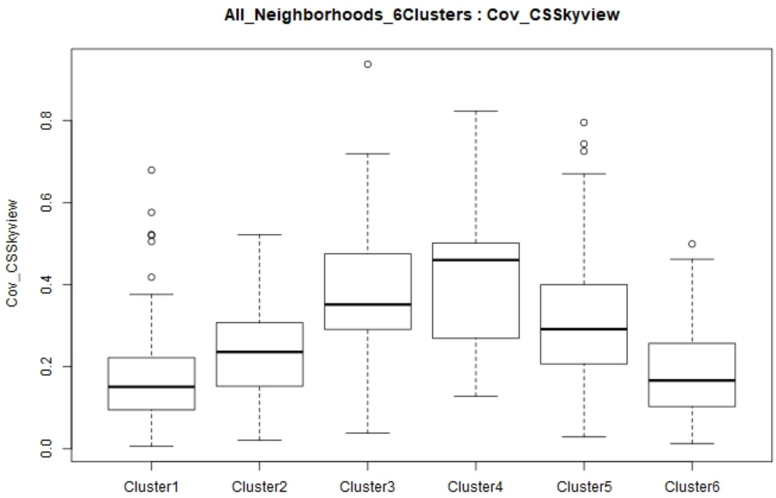


Figure 6.46 : Coefficient of Variation of CS Skyview values for all clusters.

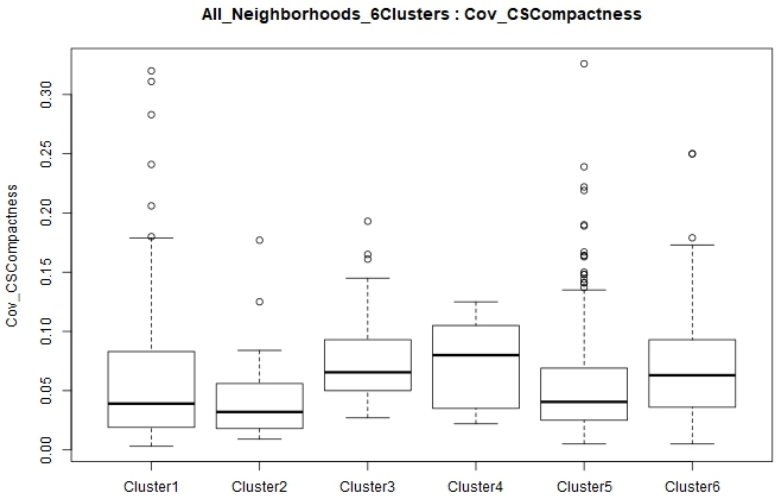


Figure 6.47: Coefficient of Variation of CS Compactness for all clusters.

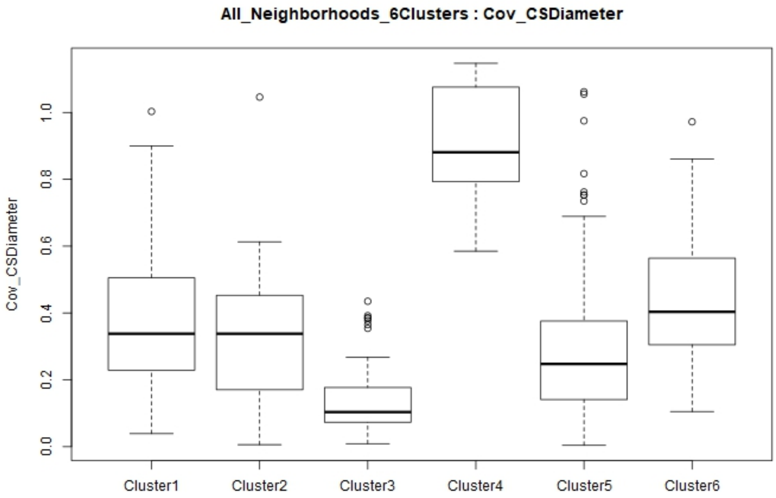


Figure 6.48 : Coefficient of Variation of CS Diameter for all clusters.

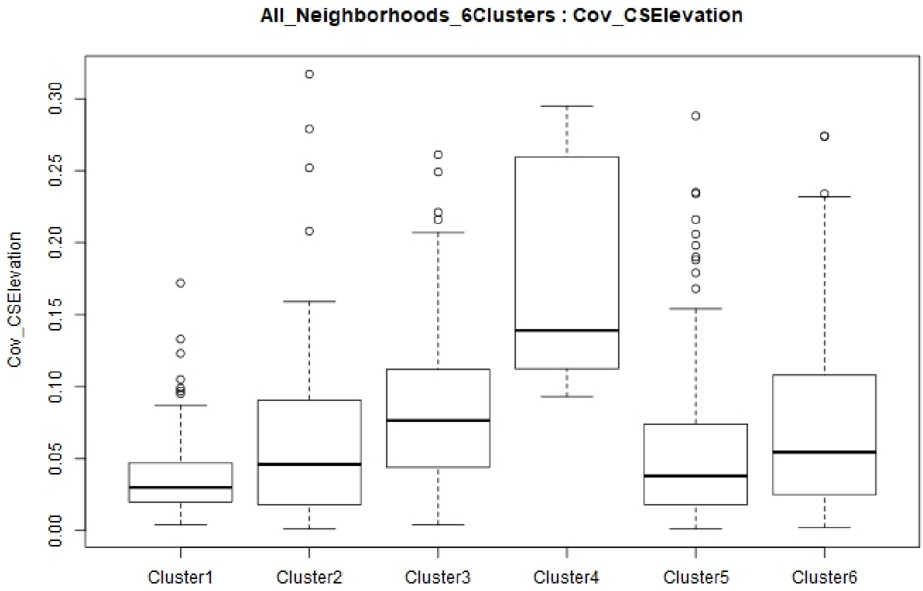


Figure 6.49 : Coefficient of Variation of Convex Space Elevation for all clusters.

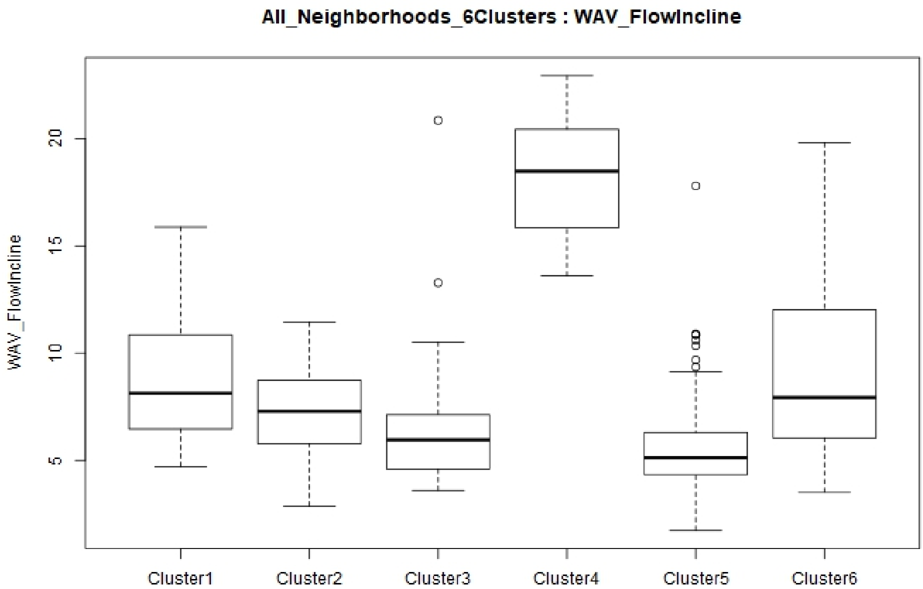


Figure 6.50 : Weighted Average of Flow Incline values for all clusters.

Cluster 5

The streets within this cluster show some of the lowest STV_Compactness and WAV_CS_Squareness values (Figures 6.21, 6.35), meaning that they represent spaces that have proportions closer to streets than squares. Several streets from all four neighborhoods fall within this cluster and are less active than those street spaces within clusters 1, 2 and 4 but are nevertheless popular and walkable.

(a) **(b)**

(c) **(d)**

Figure 6.51 : Cluster 5 images from (a) Caferaga (b) Chiado (c)Hasanpasa (d)Ajuda**.**

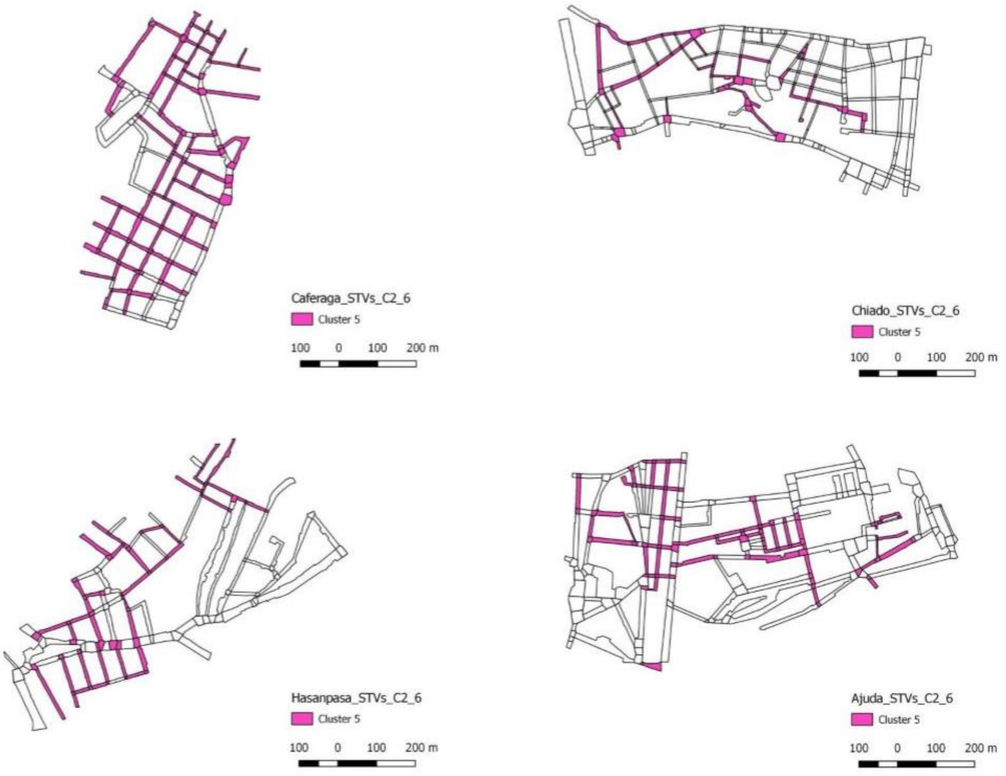


Figure 6.52: Cluster 5 maps of Caferaga, Chiado, Hasanpasa and Ajuda.

They are mainly residential with frequent ground floor commercial functions. It is worth comparing this cluster with clusters 3 and 6, as they all show similar compactness and levels of activity. Several of their morphological and Space Syntax attribute values are similar to those of cluster 3, and for both clusters they are more favorable than that of cluster 6 based on the existing walkability literature: STVs_Width (Figure 6.4), Permeability (Figure 6.6), BArea_pSTVLen, FArea_pSTVLen (Figures 6.12-6.13), STVs_Perimeter, STVs_Length (Figures 6.22-6.23), STVs_HeightTWidth (Figure 6.27), FlowLenghtTSTVArea, STVs_PerimTArea, STVs_Area, STVs_Volume, WAV_CSSkyview (Figure 6.29-6.33), STVs_Height (Figure 6.40), Cov_NFloors, Cov_CSSkyview (Figure 6.45-6.46), Cov_CSDiameter (Figure 6.48), WAV_Integration400 (Figure 6.17), WAV_Connectivity (Figure 6.34), WAV_TotalDepth400, WAV_NodeCount400 (Figures 6.38-6.39), WAV_FacadeHeight (Figure 6.42), STVs_NFacadesPerM, WAV_FacadeArea, WAV_FacadeWidth (Figures 6.55-6.57).

Aligning with general assumptions regarding these attributes in terms of how they influence walkability, streets of clusters 3 and 5 are much more active than those of cluster 6. Compared to streets of cluster 3, cluster 5's streets are slightly less enclosed; also, they are wider, accommodating double-lane car traffic while most of cluster 3 have single lane or no traffic at all. Another difference is higher granularity; the facades are narrower (Figures 6.57) and therefore change more frequently in cluster 5, yet the number of buildings and average number of floors are similar. This is likely due to additional street wall elements such as retaining or construction walls which explain lower levels of permeability detected for this cluster.

Despite lower enclosure and permeability, this cluster has the most active streets among the street-like clusters 3, 5 and 6. This is likely due to the commercial activity in this cluster, apparent in Chiado and Caferağa streets within it. It should also be noted that the permeability measure in this study is based on doors and windows recognized by computer vision and even though highly permeable, shop windows are not recognized and so, not counted.

Cluster 6

(a)

(b)

(c)

(d)

Figure 6.53 : Cluster 6 images: (a) Caferaga, (b) Chiado, (c) Hasanpasa, (d)Ajuda.

The majority of the streets this cluster represents are in the neighborhoods of Hasanpaşa and Ajuda, both of which were selected for samples considered to be less walkable. Streets in cluster 6 are the least active streets (Figure 6.1) among the samples studied; with the least favorable morphological conditions based on walkability literature. They are almost entirely residential in Ajuda and host a very limited number of commercial functions in Hasanpaşa. They are the widest, longest, least enclosed and least connected (Figures 6.4, 6.23, 6.33, 6.16, 6.17, 6.34, 6.38, 6.39) among streets within clusters 3, 5 and 6 which are the most street-like (as opposed to square-like) among the sample streets studied (Figure 6.21-6.35). Within these three clusters of 3, 5 and 6, cluster 6 includes the most number of square-like spaces, however, these spaces do not help accommodate a lively, active street life like the larger squares do as in cluster 4, both due to the very low 3d enclosure values measured by the WAV_CSSkyview attribute (Figure 6.33) and their lack of commercial activity (Figure 6.11). This cluster also has the highest value for the Negative attribute (Figure 6.25), indicating the most frequent instances of “calamity”, “abandoned” and “demolished” tags recognized in its images.

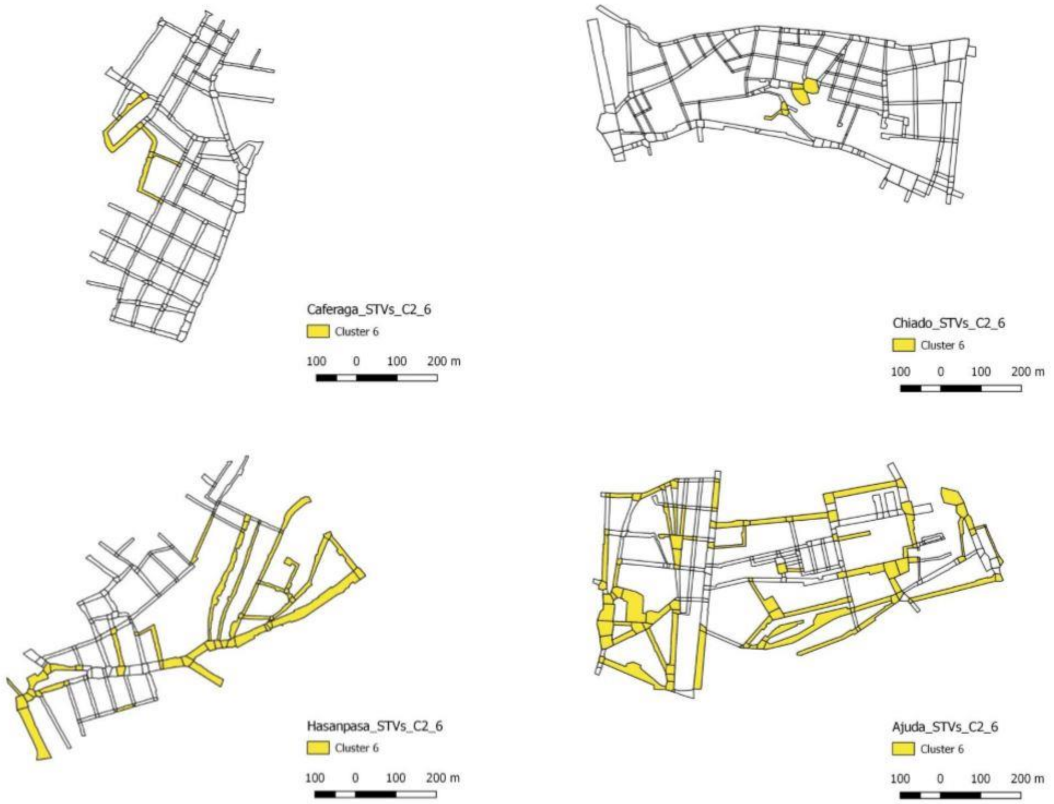


Figure 6.54 : Cluster 6 maps of Caferaga, Chiado, Hasanpasa and Ajuda.

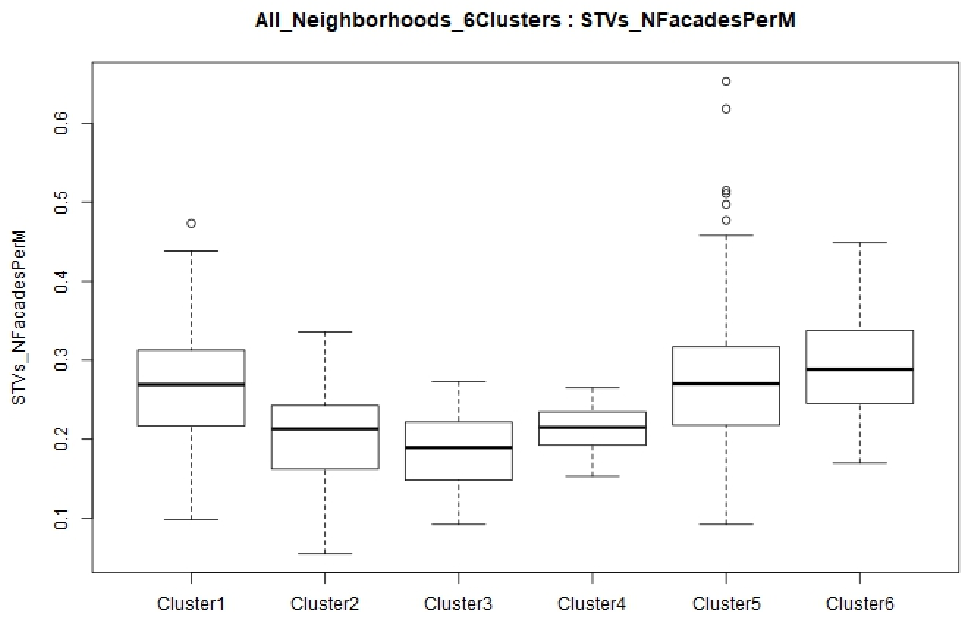


Figure 6.55 : Number of Facades per m values for all clusters.

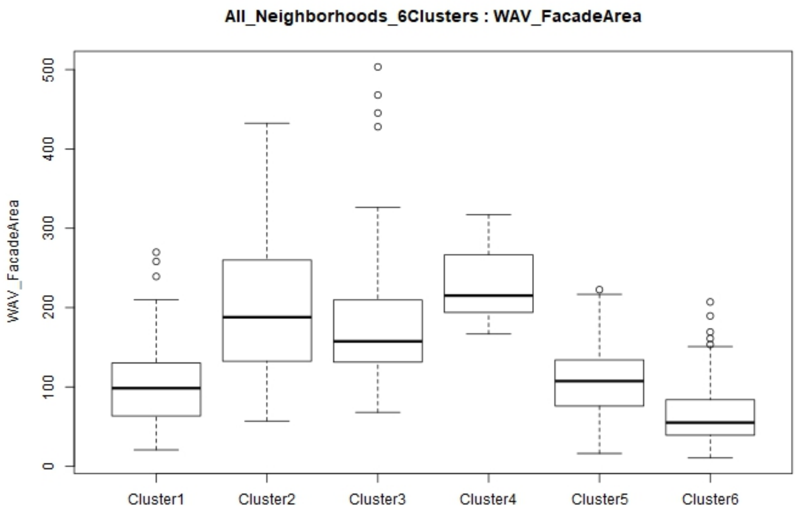


Figure 6.56 : Weighted Average of Façade Areas values for all clusters.

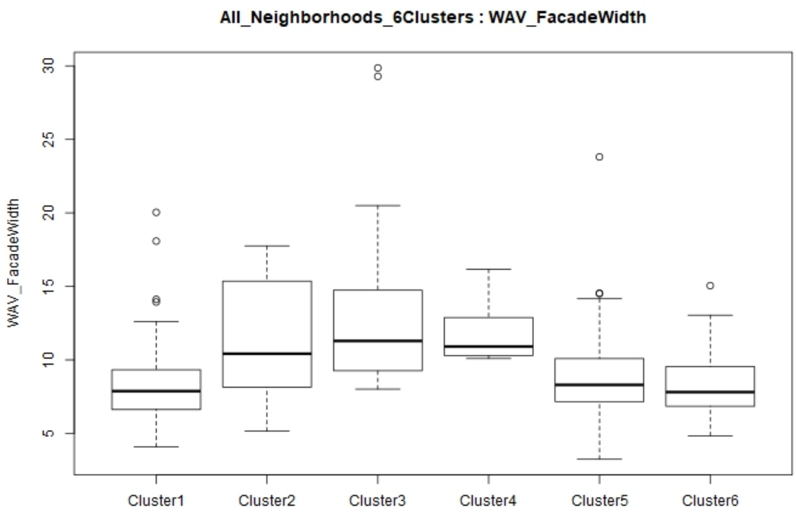


Figure 6.57 : Weighted Average of Façade Widths values for all clusters.

The narrower and smaller facades of this cluster (Figure 6.56, 6.57) do not belong to buildings as BN_pSTVLen values are similar with clusters 3 and 5 (Figure 6.26), but belong to retaining and construction walls which effect walkability negatively due to low permeability even though they seem to increase granularity. One attribute with surprisingly high values within this cluster are Enclosure (Figure 6.28) and Green (Figure 6.58). The amount of greenery on a street is expected to increase walkability, and contrary to this expectation, the streets in this cluster are considered the least walkable in the studied sample. One reason could be that this variable takes into account all kinds of visible greenery including instances where “park”, “landscape”, “environment” and “tree” were recognized whereas primarily trees, especially those with canopies are considered most influential for walkability. Enclosure indicator on the other hand measures street wall continuity in 2d and does not seem to represent enclosure as well as the CS_Skyview attribute that measures it in 3d.

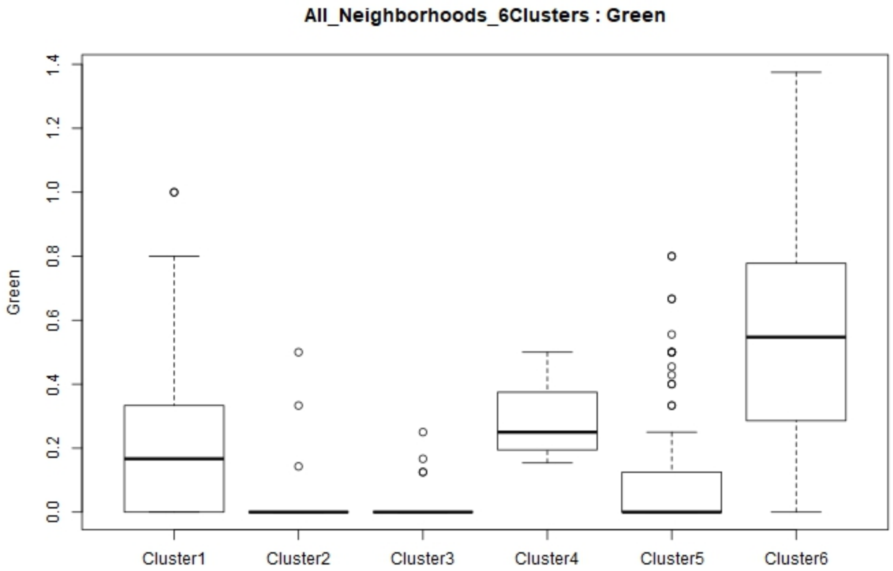


Figure 6.58 : Green indicator values for all clusters.

6.3 Defining a Final Set of Indicators

The six groups of streets studied in this chapter hardly represent all kinds of urban street typologies one can study, yet they help us understand a selection of urban street typologies identified within samples from four neighborhoods of two distinct cities with a wide-range of walkability levels. Making a comparison between the known qualities of these street space clusters and the behavior of the attributes, we evaluate how each attribute relates with walkability, and how it can be utilized.

Even though the clustering was done based on values of 22 mainly morphological indicators, the clusters' values for all indicators are explored and the most significant and representative indicators are discussed below. We look at how six different combinations of these quantitatively measured attributes result in varying levels of walkability; what can be measured effectively and really represent walkability, which works and which fails. The next step will be to formulate what can be done to most efficiently and effectively improve these conditions.

One finding that we propose will help assess urban open spaces for walkability more accurately is that the **Shape** characteristic is decisive in how street spaces should be evaluated; street-like and square-like spaces behave differently, and so should be evaluated based on different criteria. Measured through the Convex and Solid-Void method introduced in the previous chapters, the attribute of STV_Compactness easily detects this property and as is done to interpret the clusters of studied samples, can be used as the first step of a method to divide streets into two: street-like and square-like. Especially, **Scale** and **Enclosure** characteristics become more critical for street-like streets (clusters 3,5 and 6) whereas square-like ones (clusters 1, 2 and 4) can accommodate vibrant street lives with varying values for these characteristics, not necessarily aligning with the principles in walkability literature. For the **Shape** characteristic, WAV_CS_Compactness values are less representative than STV_Compactness as this indicator measures the average compactness of Convex-Void chunks rather than complete STVs. Regarding the **Scale** characteristic, STVs_Lenght, Area, Width, Height and AV_Floors are highly representative and are very relevant for walkability in street-like spaces but not as critical in square-like ones. NFacadesPerM along with WAV_FaçadeArea were found not to be effective in determining how complex and interesting facades are, looking at cluster 6 whose values show that it has smaller and more variety of façades per STV length than all other clusters even though it does not. This is due to Convex and Solid-Void method counting all faces of bounding surfaces including retaining and construction walls, and also because curvilinear walls are modeled broken into several smaller faces. This is why these two attributes do not give an accurate measure of scale or complexity based on facades as in the case for Hasanpaşa where a majority of the bounding walls are retaining or construction walls, the largest one of which follow a curved path and therefore is divided into multiple small surfaces in the 3d model. The BN_pSTVLen attribute is more accurate in measuring granularity, complexity and even a potential for diversity of functions, thus it can replace these indicators. AV_BArea values were found to be alike across all similar clusters so this indicator cannot be judged for its relationship with walkability within this sample.

Following the assessment of the **Shape** characteristic**, Diversity** measure based on use (rather than on morphology) should be utilized to determine whether the streets are residential or mixed-use as this makes a difference in how they can be more accurately assessed with our attributes. **Permeability** measured using the count of doors and windows is hard to accurately assess through this method for commercial street spaces as doors and windows cannot be detected on facades of buildings with shop windows at their ground floors even though such facades clearly make the street wall highly permeable. Instead, the attributes of Commercial and GPlaces_pSTVLen are helpful in measuring permeability. Morphological diversity, tested to be measured using NFacades_perM cannot be accurately measured due to issues with this attribute explained above. Based on these findings, the GPlaces_pSTVLen attribute should first be used to distinguish commercial and non-commercial streets and to assess diversity of uses, then the less commercially active streets can be assessed for the frequency of doors and windows using the permeability indicator.

None of the morphological attributes proposed to assess morphological **Complexity** were successful in doing so due to issues explained above regarding façade geometry modeling. BN_pSTVLen can distinguish between more and less complex and therefore interesting and attractive street-like spaces; this is demonstrated by its lower values for cluster 6 which is the least interesting, attractive and the least walkable. GPlaces_pSTVLen is effective in identifying commercial activity and is effective in measuring complexity based on functions and potential for variation in facades in all types of street spaces whether street or square-like.

Connectedness is relevant for all types of street spaces and is closely related with how active streets are regardless of their shape or diversity. WAV_Integration400 was the indicator used for clustering but all Space Syntax indicator median values show a similar pattern when their values are compared across clusters.

Physical **Density** is best measured using BArea_pSTVLen and FArea_pSTVLen and aligns with expectations for more street-like spaces of clusters 3, 5 and 6. GPlaces_pSTVLen is also informative of density regarding commercial use.

WAV_CS_Skyview is the attribute that best represents the **Enclosure** characteristic; and its expected influence on walkability strongly aligns with known characteristics of street-like spaces of clusters 3, 5 and 6. STV_HeightTWidth is also representative yet does not distinguish as strongly between clusters and FacHeigthTWidth is not representative due to issues mentioned above.

Under the characteristic of **Infrastructure**, attributes of Green and Motor-transit act contrary to expectation in regards to their influence on walkability and so the activity of street spaces. One reason for the Green indicator to be ineffective is the scarcity of data collected and the other is likely due to trees with canopies rather than the other elements counted for this attribute (landscape, environment, park) having a stronger influence on the walking experience. The effectiveness of the Pavement attribute, measuring the existence but not the quality of sidewalks cannot be judged based on the data collected for these samples as values show most street spaces to have sidewalks. Nevertheless, streets of cluster 6 have lower values that correctly reflect the lack of sidewalk infrastructure in many of its streets. The **Negative** attribute detects the visual ques for “abandonment”, “calamity” or “demolished” and its values align with the low walkability levels of cluster 6.

The **Inclination** characteristic was successfully measured by STVs_ElevChange and WAV_FlowIncline attributes yet their effect on walkability was not clearly identified among streets studied. Several street spaces known to be active and walkable studied within this research fall in clusters that have higher values for these attributes.

Table 6.10 presents the effective indicators and the types of streets they are successful in assessing. Attributes marked as limited were successful in identifying the more obviously distinguishable problems with the less walkable streets under cluster 6.

Table 6.10 : Most effective attributes and their characteristic groups.

Characteristic	Attribute	Effectiveness
Density		
Physical	**STV_BArea_p_STVLen**	**Yes, street-like spaces**
	STV_FArea_p_STVLen	**Yes, street-like spaces**
Use	**GPlaces_pSTVLen**	**Yes, all street spaces**
Diversity		
Morphological	STVs_#FacadesPerM	No
(Land) use	**GPlaces_pSTVLen**	**Yes, all street spaces**
Connectedness		
Space Syntax	**WAv_Integration400**	**Yes, all street spaces**
(Human) Scale		
	STVs_Area	**Yes, street-like spaces**
	STVs_Length	**Yes, street-like spaces**
	STVs_Width	**Yes, street-like spaces**
	STVs_Height	**Yes, street-like spaces**
	STVs_#FacadesPerM	No
	WAV_FacadeArea	No
	AV_Floors	Yes, but not parallel with walking activity
	AV_BArea	No
Complexity		
Granularity/Articulation	STVs_#FacadesPerM	No
	WAV_FacadeArea	No

Table 6.10 (continued) : Most effective attributes and their characteristic groups.

Characteristic	Attribute	Effectiveness
	BN_pSTVLen	Yes, but limited
Activity	**GPlaces_pSTVLen**	**Yes, all street spaces**
Enclosure		
	STVs_Height	No, Skyview is more representative
	STVs_Height/Width	Yes, Skyview is more representative
	WAV_FacadeHeight/Width	No, Skyview is more representative
	WAV_CS_Skyview	**Yes, street-like spaces**
Shape		
	STVs_Compactness	**Yes, all street spaces**
	WAV_CS_Compactness	No
	WAV_CS_Squareness	Yes, STV compactness more effective
	STVs_PerimTArea	Yes, but not parallel with walking activity
Permeability/Transparency		
	GPlaces_pSTVLen	**Yes, all street spaces**
	permeability	**Yes, residential streets**
	Commercial	Yes, but limited
Infrastructure Quality (and Maintenance)		
	green	No
	pavement	Yes, but limited
	motor_transit	Yes, but not parallel with walking activity
	negative	Yes, but limited

6.4 Conclusions

As a result of this research, firstly 22 attributes were identified to be consistently measurable by the proposed model and successful in quantifying walkability characteristics of the built environment identified based on literature and compared through observation, and then 11 were found to be more closely linked with observed walkability characteristics in streets of these neighborhoods classified under 6 typologies. It is proposed that these attributes can effectively measure and be used to improve walkability conditions in specific street types based on the street spaces' shapes – street or square like – and their diversity of use – residential or mixed use.

Considering the results of the predictive regression analysis presented in the beginning of the chapter and in the previous section, the relationship of these attributes with walkability is not quantitatively proven based on an outcome variable measuring actual walking activity, but is inferred based on literature and observation utilizing case studies. These measures can be improved with greater availability and accuracy of data; especially Google Street View based attributes related to **Infrastructure** (and maintenance) can be improved with better-quality street view imagery and more advanced, street-specifically trained image recognition algorithms.

From our case studies and statistical analysis, we infer that our model combining 3d morphological assessment and streetscape data collection method based on street view imagery is successful in quantitatively capturing a number of street-scale attributes that are strongly linked with walkability in well-established literature. As will be further elaborated in the final chapter of this dissertation, this is considered a first step in applying a newly developed spatial representation model along with a set of novel street assessment methods to the problem of measuring street-level walkability. While the model, methods and therefore measured attribute data should be further developed for accuracy, the statistical analysis should also be improved to obtain more conclusive results through the use of more representative data. This includes data for objectively representing the walking behavior as well as attribute data from different contexts to account for a wider range of combinations of walkability related street characteristics.

Based on these findings, the following chapter presents guidelines for assessment and improvement of urban streets in terms of walkability.

7. RECOMMENDATIONS

7.1 Introduction

The research carried out for this thesis aimed to explore remotely measurable attributes of street spaces for street and neighborhood-scale walkability. The findings show us that several characteristics of streets that affect the walking experience can be quantified through morphological and streetscape attributes. Also, social media data along with automated people counts on street view imagery can help compare how active streets are, even though they cannot be used as outcome variables in predicting walkability with the samples studied in this research. K-means clustering algorithm utilized in the previous chapter to group studied samples based on the similarity of attribute values measured yielded six clusters of street spaces that could be identified as typologies to have distinct, well-known characteristics. This identification was possible based on the streets' sizes and proportions legible on 2d maps as well as the known characteristics of these street spaces from experience. A descriptive analysis of these groups shows us that certain distinguishing characteristics make street spaces behave differently in terms of the relationship between their attributes and their levels of walkability. The distinguishing characteristics we found to be most significantly influencing the relationship between walkability and the attributes are Shape and Diversity (of use), measured most reliably by STV_Compactness and GPlaces_pSTVLen. An example to explain how these characteristics affect the attribute-walkability relationship is as follows: a square-like and commercial street space can be much wider than a street-like and residential space, and contrary to the expectation that street width is negatively correlated with walkability; can be more walkable than a narrower, street-like and residential street. Below is a detailed explanation of how we found these attributes to be determining looking at our cluster analysis in this respect.

We know from observation that among our clusters studied in the previous chapter, 1, 2 and 4 are square-like and commercial with 4 having the most commercial activity and 1 being the most mixed with residential use, 3 and 6 are mainly street-like and residential and 5 is street-like and commercial, also being highly mixed with residential use. We do not have a cluster for square-like and residential street spaces but they do exist and most fall under cluster 6. We also know that cluster 6 is the most problematic in terms of walkability from observation which we can support by the fact that most of these streets fall in Hasanpaşa or Ajuda that are our less walkable neighborhoods and that they are the least popular among the studied streets (Figure 6.1). We also know from observation and experience that cluster 1 includes some of the main streets of each neighborhood and cluster 2 has streets in Chiado connecting to the very lively squares of cluster 4; all of which are quite walkable. Cluster 5 is also mostly walkable and active, having mainly residential streets with frequent ground floor commercial amenities. Cluster 3 is much less active, but from observation is known to have well enclosed, pleasant to walk, residential streets.

To further investigate how these characteristics influenced attribute behaviors, a secondary classification was made among the STVs based on their shape, diversity of use and walkability (based on their clusters), followed by their descriptive analysis presented in Table 7.1 and as boxplots (Figures 7.1-7.10). The STVs with the highest and lowest extreme values for STV_Compactness (those above 0.6 and below 0.5), GPlaces_pSTVLen (those above 0.15 and below 0.01) and walkability (clusters 1-2-3-4-5 were considered walkable and cluster 6, not walkable) were put under 6 groups: commercial, square-like, walkable (1); commercial, street-like, walkable (2); residential, square-like, walkable (3); residential, street-like, walkable (4); residential, square-like, not walkable (5); and residential, street-like, not walkable (6). There were not enough samples for commercial and not walkable streets therefore the two classes of such street-like and square-like spaces are not represented in the boxplots.

Exploring the results of the descriptive analysis we look at the changes in value ranges of the attributes that differ significantly among the groups and determine thresholds that seem to influence walkability in a neighborhood street within its group. These threshold values are indicated by solid and dashed lines shown in the boxplots (Figures 7.1-7.10), and in Table 7.1 accompanied by values used in determining them in bold and italic, based on which we propose recommendations for urban improvement scenarios. Note that the threshold values are rounded up or down for ease of reference, also since they are not determined by precise calculations but based on value ranges. Due to lack of samples in the current classification, recommendations regarding commercial and not walkable streets that are street or square like are done based on value comparisons among clusters in the previous chapter.

The next section provides a set of guidelines to decision makers, planning and design professionals for analyzing streets in a neighborhood, and taking steps to improve walkability on these streets depending on levels of intervention and impact on walkability affordable by these improvements. The levels of interventions are grouped under planning and design; planning level addressing cases where a lower level improvement at earlier stages of a street or neighborhood’s development is possible; or where a wider scope of change is planned; and design level targeting interventions in later stages of development of existing streets with smaller scale and faster improvements.

Here we also talk about two levels of impact affordable by the suggested improvements in regard to how directly or indirectly they alter the attribute in question. The first one pertains to the physical, where the physical properties can directly be altered to improve the street. One example to this is the addition of new streets therefore shortening of the street segment lengths and block sizes and the increasing of nodes at the stage of street network design or where such interventions are possible. Another example is the reduction of building setbacks which will reduce the street width and street space areas. These are direct physical alterations that are usually difficult to implement, especially at later stages of planning or to existing neighborhoods, if plan alterations are possible at all. Improving the sidewalk would be a physical intervention in the design level. Perceptual level impact refers to the smaller changes targeting how street spaces are perceived, indirectly affecting the attribute in question. Most perceptual impact is possible through design level interventions that can be applied retrospectively, to existing built environments and are easier, faster and cheaper to implement. An example would be to plant trees and install street furniture to decrease the perceived street widths and lengths by increasing the articulation of space. If we were talking about the Green or Street Furniture attributes however, we would consider these as physical level interventions as they would be directly physically altering these attributes.

While there are certainly many more issues that can be dealt with to improve walkability than mentioned here, this chapter summarizes the specific interventions that can be recommended based on the consistently measurable attributes that have been inferred from the current study. Additional issues not dealt with here include climatic comfort, universal accessibility and issues requiring larger-scale intervention such as the accessibility of recreational, educational, religious and cultural facilities as well as transportation.

The threshold values, what they mean for walkability and how they can be utilized in planning and design scenarios are summarized as recommendations below.

7.2 Steps for Urban Improvement

As was done to explore our samples, we propose that the street spaces to be evaluated for walkability should be done so by grouping them in terms of two attributes: STV_Compactness, determining how square-like or street-like a street space is; and GPlaces_pSTVLen or Google Place location frequency which we use to measure the level of mixed-use. Based on these, we can think of streets in four groups that are square-like and commercial; street-like and commercial; square-like and residential, and street-like and residential. Here the groups are referred to as “walkable” and “not walkable” for ease of understanding, they are not grouped based on any numeric value but solely based on their cluster’s known level of activeness and walkability-related qualities conforming with literature.

The recommendations also provided in the form of a table to be utilized as steps from top to bottom are presented following the detailed explanations (Table 7.2).

First, a Space Syntax analysis is to be run within a 400m radius of the street(s) to be improved along with the street view image analysis of the pavements for the same street network. If a planning intervention is possible, the street network should be improved and if more limited intervention is possible, sidewalks should be built or improved for the street segments of the highest impact in the street network as well as the street segment to be improved itself. With the model used in this research, it is possible to do a parametric analysis of the street network allowing for instant alteration and testing of the impact the addition of a segment will have on the overall network **Connectedness** as described in the methodology chapter. If this analysis is applied to the network consisting only of the segments with sidewalks, and iteratively repeated by adding segments without pavements that can be improved, it would be possible to identify which segments would impact the network connectivity most and plan for sidewalk improvements based on the results. One additional approach found in guidelines is to start improvements from street segments where there are transit stops; access to transit is critical for walkability due to all public transport users also being walkers at the origins and destinations of their routes covered by public transit (Cornog & Gelinne, 2010). While the remote measuring method used in this study does not distinguish between good and bad quality pavements, many recent studies allow for the remote detection of the quality of sidewalk features like curb cuts (Abbott et al., 2018) using deep learning methods with crowd-sourced street view image labels. When, as foreseen for the future of this research, this part of the model is improved through such techniques, or where detailed data on sidewalk quality is an available, more in-depth improvement scenarios should be considered. One very comprehensive guide for sidewalk improvements is provided by the Global Designing Cities Initiative and National Association of City Transportation Officials (National Association of City Transportation Officials, 2019) where the sidewalk space is considered to have 4 zones in the following order: frontage zone (immediately at the front of and servicing buildings), pedestrian through zone (the area that should be clear for pedestrian flow), street furniture/curb zone (where benches, newsstands, bike racks, street-lights should be provided) and buffer zone (designated to bike lanes, curb extensions, storm water management elements). If possible, each zone should be improved to accommodate designated functions in the best way and be revised in the extension or addition of a zone or street-element.

Then, as was found widely definitive for the relationship between the physical characteristics and walkability of street spaces, it is recommended that street space compactness or in other words how square-like or street-like a street space is should be assessed using the STVs_Compactness attribute. All following attribute measures should be evaluated based on a street space's **Shape** measured by this attribute. We determine 0.7 as the threshold value under which the spaces are considered as street-like and the others as square-like.

Next, street segment lengths; or in other words: the path distances along streets from one intersection to the next is to be assessed using the STVs_Length attribute. This should only be applied to street-like spaces as multiple clusters mainly consisting of square-like spaces considered walkable (1, 2, 4) show a wide range of street lengths. Based on the value range (Figure 7.1) comparisons, a length of 100 m is determined as the threshold over which a street's walkability is negatively affected. Larger scope planning level interventions can once again modify the street network by adding segments in the form of streets or if that is not possible, walking paths. Design interventions to decrease perceptual distances can include using larger scale street elements such as trees, newsstands, bus shelters or commissioned street art as well as encouraging outdoor use for ground-level amenities of surrounding buildings and designating sidewalk spaces for street vendors. To ease navigation that may be negatively affected by the lowered visibility of street connections due to increased distances, signage can be utilized.

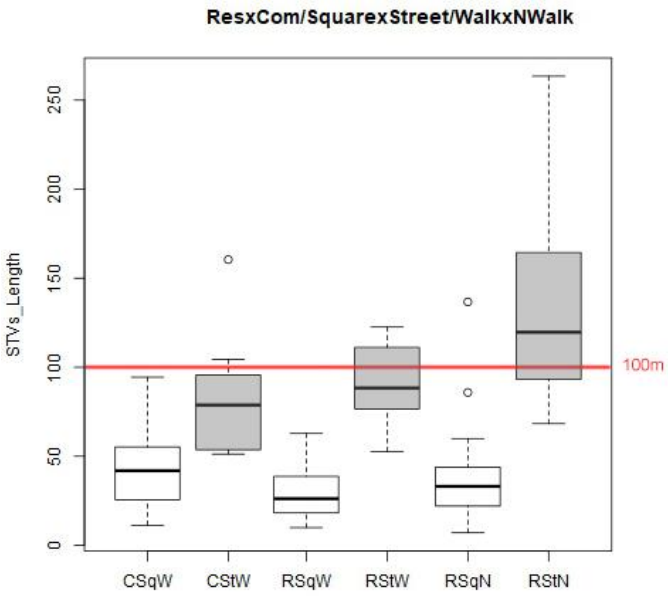


Figure 7.1 : Value threshold for STVs_Length. C: Commercial, R: Residential, St: Street-like, Sq: Square-like, W: Walkable, N: Not walkable.

Street width, related with the characteristics of **Scale** and **Enclosure** as also apparent in literature is critical for walkability but one of the findings of this research is that it has more significant impact on street-like spaces. Based on the value ranges (Figure 7.2), street-like streets wider than 10m should be improved by decreasing building setbacks in the planning level, or by design interventions to decrease perceptual width.

At later stages of development or in addition to this, the number of traffic lanes can be decreased and this space can be reclaimed for pedestrian and bicycle use by extending sidewalks, building bike lanes and enlarging refuge islands to enhance pedestrian crossings.

The enlarged sidewalk spaces can be improved by special attention to the varying requirements of all four sidewalk zones as explained above. In addition to these improvements, outdoor use by ground floor amenities of buildings can be encouraged; street space can be designated for use by street vendors and parklets can be utilized. Perceptual width can be controlled by larger scale street furniture and features like trees, newsstands, bus shelters, lighting and commissioned street art.

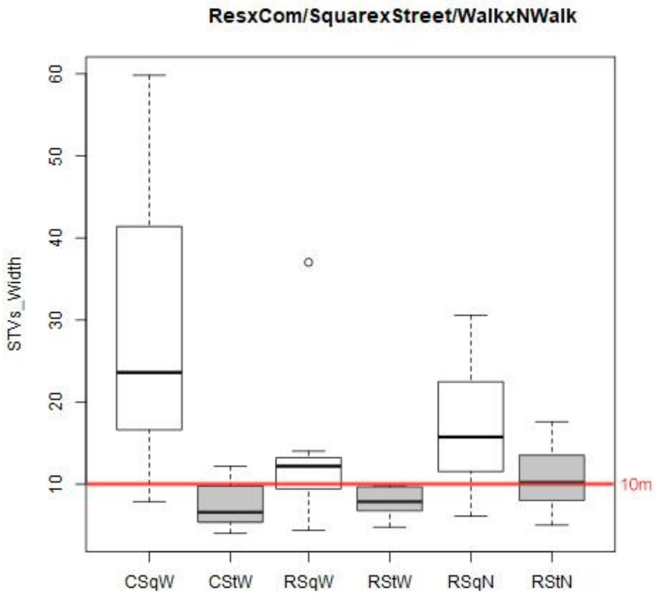


Figure 7.2 : Value threshold for STVs_Width. C: Commercial, R: Residential, St:Street-like, Sq: Square-like, W: Walkable, N: Not walkable.

In the neighborhoods studied for this research, the predominant uses were residential and commercial therefore we are able to assess cases where most streets are residential or commercial, acknowledging that multiple other uses are possible. On the other hand, it is common in literature to measure mixed-use by the percentage of commercial and residential square meters since we know that residential use brings on an active street life outside weekday work hours and commercial uses keep the street lively throughout the day and also at night based on the type of commercial activity.

In this study we measure the level of mixed-use by the number of Google Place locations per street length and also use it as a distinguishing property in grouping street spaces for applying different attribute assessments. We have found within our samples that if this value is below 0.2 which mean 2 locations every 10 meters, the street can be considered as residential or non-commercial and if this value is higher, as commercial. We recommend that for streets that are found to be residential, mixed-use should be encouraged to facilitate a more active street life throughout the day.

Based on the cluster values (cluster boxplot) for this attribute comparing clusters 3 and 6 which are both residential and street-like, we can say that those streets that have at least 1 commercial location every 20m can still be walkable but below that, our samples become less so. To improve this, commercial uses can be designated for the ground floors in the planning stage. And for the design stage, the influence of existing ground floor amenities can be expanded and temporary outdoor uses can be encouraged such as block parties, stoop sales and other community gatherings.

STVs_Area, a measure of the **Scale** characteristic, is relevant for all types of spaces may they be square or street-like, commercial or residential. Our samples suggest that most walkable and active spaces remain below 1000 m2 unless they are commercial squares in Chiado in which case they average around 2000 m2 (Figure 7.3) and are still are very lively street spaces. However, they become problematic over 500 m2 in the case that they are residential squares as in Hasanpaşa and Ajuda. We recommend that residential squares over 500m2 as well as residential and commercial street-like spaces over 1000m2 can be improved by scaling down in planning level and perceptually in the design level. Physical interventions mentioned for STVs length and width can be applied in all cases. Additionally, programming of these public spaces become critical if the built environment does not naturally provide adequate levels of **Density** and **Enclosure** which is a consequence of larger scale street spaces. Designating street spaces to street vendors, encouraging outdoor seating, pop-up stores, community gathering and commercial events like farmers' markets, second-hand markets and open-air art events are some examples to such interventions.

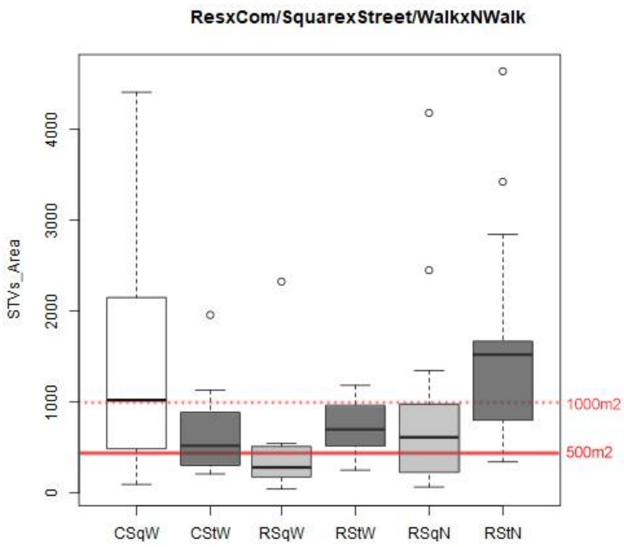


Figure 7.3 : Value thresholds for STVs_Area. C: Commercial, R: Residential, St:Street-like, Sq: Square-like, W: Walkable, N: Not walkable.

AV_Floors, STVs_Height and WAV_CS_Skyview deal with the related issues that the characteristic of **Enclosure** is concerned with in the three dimensions. AV_Floors is solely dependent on buildings' number of floors while STVs_Height takes into account all modeled elements that affect the feeling of enclosure in a street space which include the street walls, buildings as well as the neighboring street-space values in the current study. WAV_CS_Skyview calculates visible sky percentage by ray-casting. We recommend that all urban street spaces should accommodate buildings with at least 3.5 floors and 4 floors if they are residential and square-like (Figure 7.4).

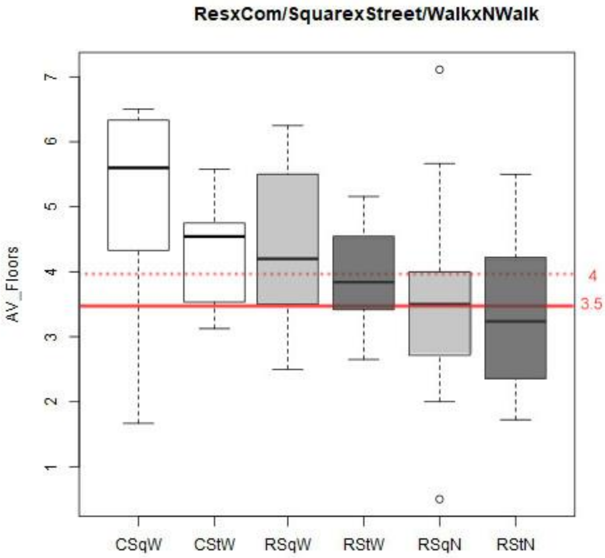


Figure 7.4 : Value thresholds for AV_Floors. C: Commercial, R: Residential, St:Street-like, Sq: Square-like, W: Walkable, N: Not walkable.

This is only relevant for the planning stage. STVs_Height should at least be 5 meters for residential and street-like spaces, 4 for residential and square-like spaces and on average 4.8 meters for commercial spaces (Figure 7.5). For WAV_CS_Skyview, values over 0.6 in general, those over 0.5 for residential street-like spaces and 0.55 for residential square-like spaces were measured for less walkable samples (Figure 7.6). For these indicators, along with building heights to be planned accordingly in the planning stage, additional design and planning interventions to strengthen enclosure can be utilized. Large setbacks with street or garden walls can be avoided as these elements decrease STVs_Height and sky view values influencing perceptual enclosure as well as permeability negatively. Street trees with large canopies as well as street furniture can be used to enhance perceived enclosure levels. Empty lots can be discouraged with tax penalties and temporary uses can be encouraged for such street spaces.

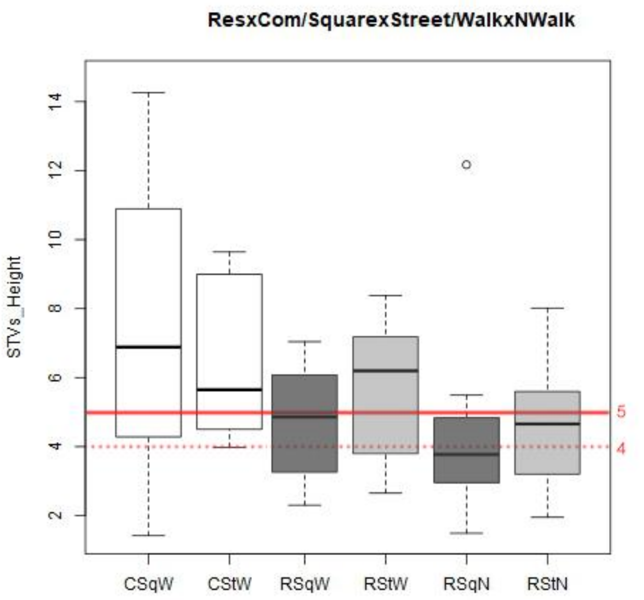


Figure 7.5 : Value thresholds for STVs_Height. C: Commercial, R: Residential, St:Street-like, Sq: Square-like, W: Walkable, N: Not walkable.

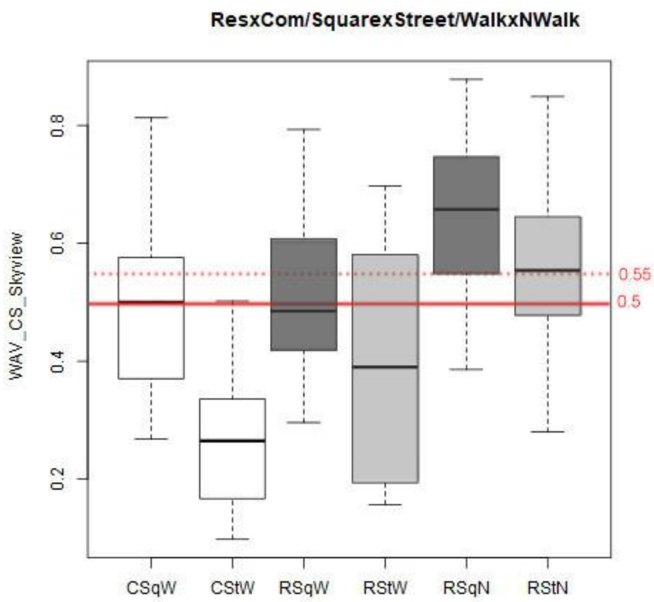


Figure 7.6 : Value thresholds for CS_Skyview. C: Commercial, R: Residential, St:Street-like, Sq: Square-like, W: Walkable, N: Not walkable.

Both measures of **Density**, BArea_pSTVLen is concerned with total built area per street length and FArea_pSTVLen measures total floor area per street length. Built area values below 25m2 for all street spaces and 45m2 for residential squares begin to influence street popularity negatively and imply less walkable clusters (Figure 7.7). For floor areas, 80m2 per street length can be considered as the minimum for all street spaces in general while streets that are less walkable fall below 100m2 for residential street-like spaces and 150m2 for residential square-like spaces (Figure 7.8). These are relevant for planning stages. In addition to regulating built areas, discouraging empty lots and wide setbacks are applicable planning and design interventions.

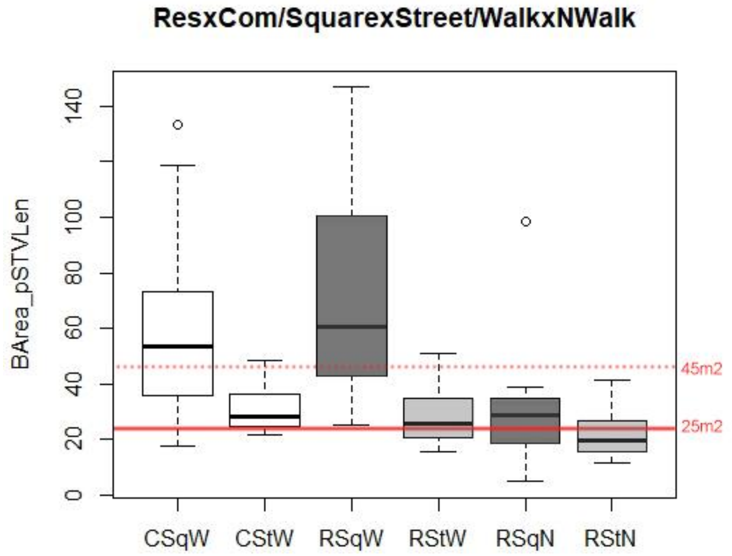


Figure 7.7 : Value thresholds for BArea_pSTVLen. C: Commercial, R: Res., St: Street-like, Sq: Square-like, W: Walkable, N: Not walkable.

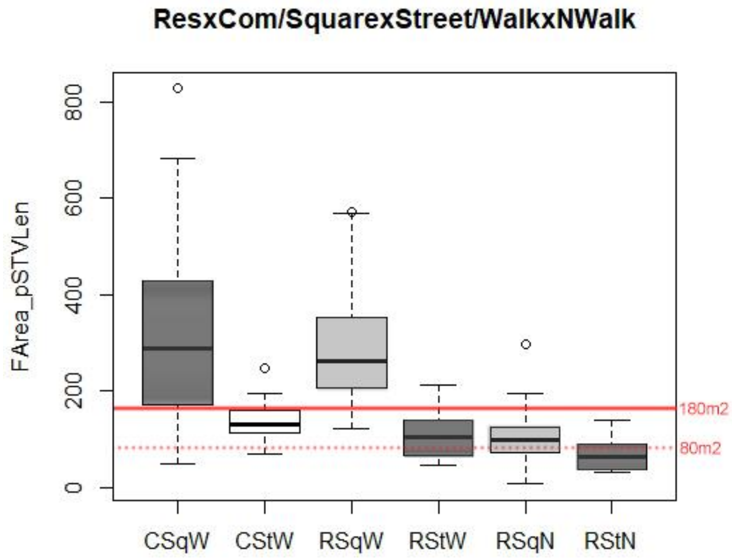


Figure 7.8 : Value thresholds for FArea_pSTVLen. C: Commercial, R: Resident., St: Street-like, Sq: Square-like, W: Walkable, N: Not walkable.

While the measuring of the permeability attribute proved problematic for commercial facades in this study, within residential streets, this value was found to be below 1.2 for street-like and 1 for square like street spaces (Figure 7.9). So, while commercial store and restaurant windows as well as outdoor seating positively influence street liveliness by increasing **Transparency**, for residential streets, the frequency of windows and doors as well as their sizes – even though not measured in this study- have an impact on this characteristic.

Besides planning for narrower lots to increase frequency of entrances, façade design regulations to increase window and door areas, decreasing setbacks, avoiding street walls and fences are applicable measures to improve transparency.

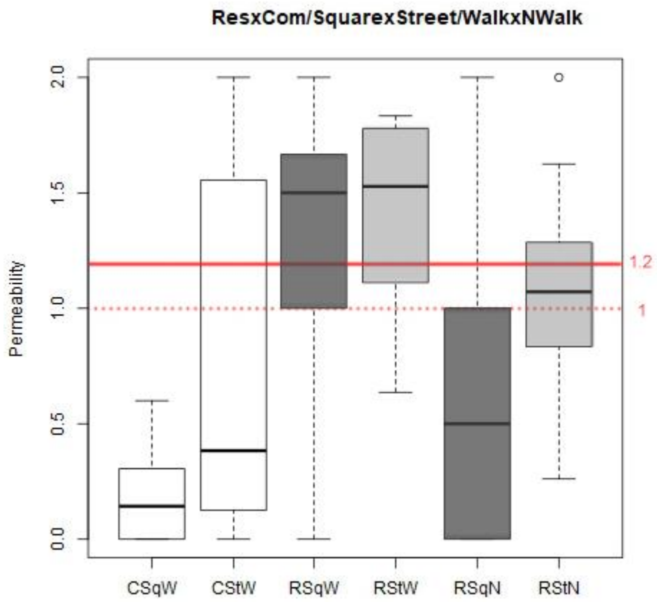


Figure 7.9 : Value thresholds for Permeability. C: Commercial, R: Residential, St: Street-like, Sq: Square-like, W: Walkable, N: Not walkable.

Finally, the measure for attribute 'Negative' that counts and averages the instances where the terms "calamity", "abandoned" or "demolition" can be identified on street view images can be employed to detect and fix **Maintenance** related issues concerning walkability. In the current study, the street-like and square-like spaces show consistency for this variable within their groups, even though square-like spaces generally show lower values (Figure 7.10). This could be due to either such negative features being less easily detected from a distance as is the case for square-like spaces or that squares are better maintained in general. Besides better maintenance measures such as more frequent collection of garbage, better designed and more accessible placement of garbage bins; encouragement to use transparent, wire gates instead of solid ones for visibility of stores even when closed and penalties for empty buildings and lots can be utilized to mitigate the impact of these issues on walkability. Temporary uses to benefit the local community can be encouraged for empty buildings and lots.

It should be noted that the threshold values proposed in the recommendations were identified looking at the descriptive analyses that were interpreted based on literature findings and known characteristics of the studied street spaces. Without interpretation and support of literature, it would not be healthy to recommend these values for design and planning as there exists a wide range of phenomena that affect how popular, active and walkable street spaces are that none of these attributes can determine alone. This is why it should be emphasized that we do not look at each attribute's value range in an isolated manner and derive conclusions, but make street classifications based on measured attributes and use their comparisons to obtain quantitative information. A practical application of this information to planning and design scenarios were presented in this chapter with the purpose of demonstrating how the proposed method can be used for classification of streets which can be used for their evaluation comparatively and for applying quantitative findings to design and planning scenarios. Ultimately, more cases should be studied to expand the range of data studied and predictive analysis based on more reliable walking activity data should be utilized to determine definitive quantitative information.

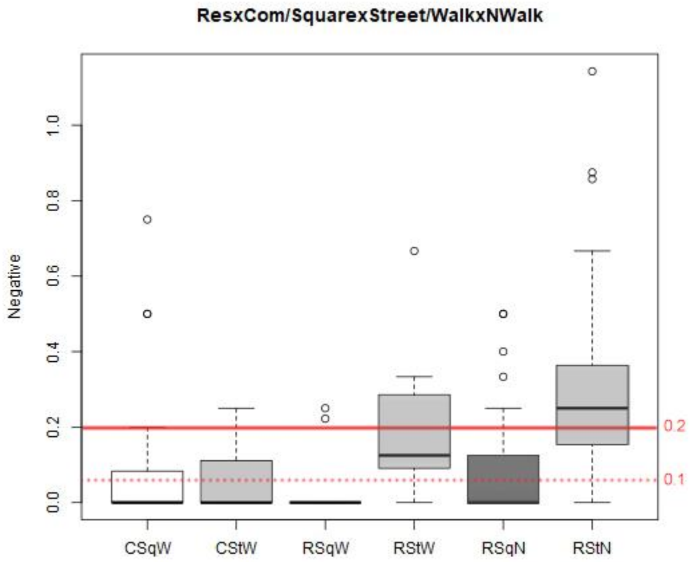


Figure 7.10 : Value thresholds for Negative. C: Commercial, R: Residential, St: Street-like, Sq: Square-like, W: Walkable, N: Not walkable.

Great guides with comprehensive recommendations to improve urban streets have already been published supported by studies in local (Cornog & Gelinne, 2010; Methorst et al., 2010; *Urban Street Design Guide*, 2013) and global contexts (*Global Streets Design Guide*, 2016; Institute for Transportation and Development Policy, 2018; National Association of City Transportation Officials, 2019).

Table 7.1 : Five number summaries of selected attributes.

Attribute	Class	min	Q1	med	Q3	max	Walkability Threshold
STVs_Area	ComSqW	94.902	485.464	1020.803	2150.055	4407.321	**below 500m2 for residential and square-like,**
	ComStW	210.040	304.492	***520.072***	***886.395***	1958.196	
	ResSqW	43.326	177.352	**281.852**	**511.362**	2325.363	***below 1000m2 for street-like***
	ResStW	251.484	518.494	***699.641***	***965.199***	1183.874	
	ResSqNW	66.002	227.145	**613.085**	**973.042**	4180.370	
	ResStNW	342.538	799.829	***1521.897***	***1668.460***	4180.370	
STVs_Length	ComSqW	11.305	25.599	41.907	55.250	94.406	**below 100m for street-like**
	ComStW	51.258	53.705	**78.784**	95.668	160.449	
	ResSqW	9.954	18.204	26.201	38.696	62.802	
	ResStW	52.725	76.599	**88.350**	111.116	122.580	
	ResSqNW	7.047	22.041	33.078	43.931	136.723	
	ResStNW	68.328	93.178	**119.672**	164.417	136.723	
WAV_CS_Skyview	ComSqW	0.268	0.3705	0.5	0.576	0.813	**below %0.55 for residential and square-like,**
	ComStW	0.098	0.167	0.265	0.336	0.502	
	ResSqW	0.296	0.418	**0.485**	0.608	0.793	***below %0.5 for residential and street-like***
	ResStW	0.157	0.194	***0.39***	0.581	0.697	
	ResSqNW	0.386	0.548	**0.6575**	0.747	0.878	
	ResStNW	0.28	0.478	***0.554***	0.645	0.878	
STVs_Width	ComSqW	7.880	16.611	23.607	41.397	59.828	**below 10m for street-like**
	ComStW	3.994	5.383	**6.576**	**9.782**	12.204	
	ResSqW	4.353	9.444	12.185	13.215	37.027	
	ResStW	4.770	6.749	**7.860**	**9.658**	9.807	
	ResSqNW	6.089	11.547	15.744	22.481	30.575	
	ResStNW	5.013	8.016	**10.225**	**13.519**	30.575	
STVs_Height	ComSqW	1.419	4.283	6.885	10.896	14.255	**above 4m for residential and square-like,**
	ComStW	3.980	4.501	5.648	8.996	9.642	
	ResSqW	2.305	3.259	**4.858**	6.078	7.041	***above 5m for residential and street-like***
	ResStW	2.651	3.798	***6.198***	7.182	8.383	
	ResSqNW	1.489	2.960	**3.772**	4.832	12.170	
	ResStNW	1.952	3.203	***4.657***	5.596	12.170	

Table 7.1 (continued) : Five number summaries of selected attributes.

Attribute	Class	min	Q1	med	Q3	max	Walkability Threshold
AV_Floors	ComSqW	1.667	4.330	5.600	6.333	6.500	**above 3.5 for residential and street-like,** ***above 4 for residential and square-like***
	ComStW	3.125	3.533	4.542	4.750	5.577	
	ResSqW	2.500	3.500	***4.200***	5.500	6.250	
	ResStW	2.650	3.417	**3.840**	4.545	5.158	
	ResSqNW	0.500	2.714	***3.500***	4.000	7.111	
	ResStNW	1.722	2.355	**3.235**	4.222	7.111	
BArea_pSTVLen	ComSqW	17.451	35.890	53.339	73.061	133.144	**above 45m2 for residential and square-like,** ***above 25m2 for residential and street-like***
	ComStW	21.813	24.730	28.069	36.167	48.572	
	ResSqW	25.269	42.825	**60.403**	100.276	146.752	
	ResStW	15.813	20.952	***25.735***	34.623	50.970	
	ResSqNW	4.873	18.506	**28.699**	35.087	98.619	
	ResStNW	11.376	15.794	***19.936***	26.528	98.619	
FArea_pSTVLen	ComSqW	48.553	170.580	288.205	429.868	827.835	**above 80m2 for street-like,** ***above 180m2 for residential and square-like***
	ComStW	68.162	**112.698**	**131.460**	160.116	248.993	
	ResSqW	121.007	***205.807***	***262.818***	351.778	572.330	
	ResStW	45.434	65.841	**105.833**	140.545	211.316	
	ResSqNW	7.127	73.864	***97.754***	***124.390***	295.937	
	ResStNW	30.585	38.708	**63.199**	90.955	295.937	
Permeability	ComSqW	0.000	0.000	0.143	0.306	0.600	**above 1 for residential and square-like,** ***above 1.2 for residential and street-like***
	ComStW	0.000	0.125	0.383	1.556	2.000	
	ResSqW	0.000	1.000	**1.500**	1.667	2.000	
	ResStW	0.636	1.111	***1.528***	1.778	1.833	
	ResSqNW	0.000	0.000	**0.500**	1.000	2.000	
	ResStNW	0.261	0.833	***1.071***	1.286	2.000	
Negative	ComSqW	0.000	0.000	0.000	0.083	0.750	**below 0.2 for residential and street-like,** ***below 0.1 for residential and square-like***
	ComStW	0.000	0.000	0.000	0.111	0.250	
	ResSqW	0.000	0.000	***0.000***	0.000	0.250	
	ResStW	0.000	0.091	**0.125**	0.286	0.667	
	ResSqNW	0.000	0.000	0.000	***0.125***	***0.500***	
	ResStNW	0.000	0.154	**0.250**	0.364	0.500	

This study does not aim to replace these guides but is intended to be used together with them specifically in cases where smaller scale street and neighborhood qualities related to walkability is to be assessed in remote locations or for study areas covering large urban regions that are impractical to measure by on-site surveys. As more cities including Helsinki, London, Singapore, Chicago and Hamburg build and utilize "digital twin" 3d city models with the advance of modeling software, scanning and remote sensing technologies (Cousins, 2017), the method proposed here becomes more relevant, due to relying on 3d city models to provide the most up-to-date morphologic evidence regarding street spaces, and present potential to become a part of evaluation methods that feedback information to the planning, design and managing processes.

The context of studied samples, the accuracy and extent of data as well as the utilized measuring methods pose certain limitations to the current research that are discussed in detail in the following chapter.

Table 7.2 : Recommended steps for street evaluation and improvement.

Attribute		**Analyze**		**Improve**			
	Characteristic			**Levels of Intervention**		**Level of Impact**	
				Planning Level	**Design and Administrative Level**	**Planning Level**	**Design and Administrative Level**
Space Syntax **WAV_Integration400**	**Connectivity**	All STV path network and STV path network with pavements		Improve street network for higher connectivity.		X	
Pavement	**Infrastructure**	All STVs (All Street Spaces)			Improve streets w.o pavements that are most critical for the street network.		X
STV_Compactness **>0.7 = Square-like** **<0.7 = Street-like**	**Shape**	All STVs Square-Like	Street-Like	Increase connections within street-like spaces that are >100m.	Decrease perceptual length of street-like spaces by increasing articulation.	X	X
STVs_Length	**Scale**	Square-Like X	Street-Like >100 m	Increase connections within street-like spaces that are >100m.	Decrease perceptual length of street-like spaces by increasing articulation.	X	X

Table 7.2 (continued) : Recommended steps for street evaluation and improvement.

Attribute	Analyze					Improve			
	Characteristic					Levels of Intervention		Level of Impact	
						Planning Level	Design and Administrative Level	Planning Level	Design and Administrative Level
STV_Width	**Scale, Enclosure**	Square-Like X		Street-Like >10 m		Decrease physical and accessible width by decreasing setbacks, widening sidewalks, adding and widening curbs at crossings.	Decrease perceptual width by planters, trees, street furniture.	X	X
GPlaces_pSTVLen **>0.2 = Commercial/ Mixed use** **<0.2 = Residential/ Other**	**Diversity, Complexity**	Square-Like Commercial X	Residential <0.05	Street-Like Commercial X	Residential <0.05	Land use change for ground floor amenities.	Encourage transparent facades.	X	X
STVs_Area	**Scale**	Sq-Com X	Sq-Res >500m2	St-Com >1000m2	St-Res >1000 m2	Decrease physical area. Use improvements for STVs_ Length and STVs_Width	Decrease perceptual area. Use improvements for STVs_ Length and STVs_Width		X

Table 7.2 (continued) : Recommended steps for street evaluation and improvement.

Attribute	Analyze					Improve			
	Characteristic					Levels of Intervention		Level of Impact	
						Planning Level	Design and Administrative Level	Planning Level	Design and Administrative Level
STVs_Height	**Enclosure**	Sq-Com <5.5	Sq-Res <4	St-Com <5.5	St-Res <5.5	Increase allowable floors.		X	
WAV_CS_Skyview	**Enclosure**	Sq-Com >0.6	Sq-Res >0.55	St-Com >0.6	St-Res >0.5	Use penalty for empty lots, encourage built area. Increase allowable floors.	Increase perceptual enclosure by planters, trees, street furniture and street art.	X	X
AV_Floors	**Enclosure, Density**	Sq-Com <3.5	Sq-Res <4	St-Com <3.5	St-Res <3.5	Use penalty for empty lots, encourage built area. Increase allowable floors.		X	
BArea_pSTVLen	**Density**	Sq-Com <25 m2	Sq-Res <45m2	St-Com <25m2	St-Res <25m2	Use penalty for empty lots, encourage built area.		X	

Table 7.2 (continued) : Recommended steps for street evaluation and improvement.

Attribute	Analyze					Improve			
	Characteristic					Levels of Intervention		Level of Impact	
						Planning Level	Design and Administrative Level	Planning Level	Design and Administrative Level
FArea_pSTVLen	**Density**	Sq-Com <80 m2	Sq-Res <180m2	St-Com < 80m2	St-Res <80m2	Use penalty for empty lots, encourage built area. Increase allowable floors.		X	
Permeability	**Transparency**	Sq-Com X	Sq-Res <1	St-Com X	St-Res <1.2	Decrease setbacks, discourage street walls.	Improve facades: encourage visible entrances and windows.	X	X
Negative	**Infrastructure**	Sq-Com X	Sq-Res >0.1	St-Com >0.1	St-Res >0.2	Maintain streets better, use penalty for empty lots and buildings, encourage transparent gates for visible store fronts.		X	

8. CONCLUSION AND DISCUSSION

The main goal of the research was to develop a walkability assessment workflow to support designers, planners, public authorities and private developers in their urban improvement decision processes. It was motivated as a response to the shortcomings of existing walkability assessment methods in terms of analyzing 3d aspects in the neighborhood and street scale as well as impracticalities in their data acquisition methods. This chapter will present the goals achieved and the contributions of the research carried out, limitations and future work that is intended to depart from the outcomes of this study.

8.1 Achievements and Contributions

This thesis proposes a method to evaluate walkability based on the neighborhood and street-level physical attributes of the urban built environment utilizing a semi-automated, parametric workflow relying on remotely accessible, geographically extensive and up-to-date urban data. The 3d urban morphology at neighborhood and street scale is set forth as the manifestation of the multiple contributors that shape the streetscape and a core set of morphological attributes are inferred as the most representative and reliably measurable through this method for walkability. A 3d open urban space representation model (Beirão et al., 2015, 2014; Čavić, 2018; Čavić et al., 2017; Sileryte et al., 2017) was utilized to compute several morphological attributes based on topography, buildings and other urban limits; and Google Street View images were analyzed using an image recognition algorithm to further articulate the streetscape morphology by identifying greenery, façade openings, street furniture, motor transit elements as well as negative aspects such as abandoned or demolished buildings. Four case studies were employed within the contexts of Istanbul and Lisbon to compute multiple morphological attributes and statistical analyses were carried out to derive a reduced set of measurable attributes. Through case studies, ranges were determined for these attributes that are deemed to indicate various levels of walkability based on the known conditions of the studied neighborhoods and street typologies.

The general theoretical contribution of the thesis is (1) the idea that a street-level morphological analysis of urban open spaces can reveal and explain a substantial set of features that contribute in the walkability of streets and neighborhoods. Following this idea, (2) a concise set of walkability-related morphological attributes measurable through remotely obtainable data were identified based on which decision-making processes be informed in neighborhood level urban improvement efforts. In doing this, (3) data sources to be utilized that are most accessible, updatable and geographically extensive were identified which also hold potential to further improvement in terms of accuracy, availability and ease of processing with the advancement of relevant technologies. (4) A semi-automated and parametric workflow was developed incorporating a GIS and 3d model-based morphological analysis in the neighborhood scale that is further articulated using Google Street View data and image recognition algorithms to evaluate walkability. (5) A first application of the GIS and 3d model based morphological analysis model; Convex and Solid-Voids was demonstrated on the analysis of walkability. (6) Specific attributes concerning the street space characteristics of shape and diversity were identified that enable a classification so that different attributes and value ranges are suggested to be used in the assessment of different classes of street spaces. (7) A set of urban design recommendations were developed for local municipality-level urban improvement scenarios targeting the betterment of walkability conditions in newly designed and urban improvement projects.

The street-level morphological analysis presented in this research links morphological street features with walkability by compiling an extensive set of measures identified from literature and then reducing them comparatively through case studies and statistical analysis. Morphological attributes have never been grouped under characteristics defined primarily by these measures, as opposed to existing research where characteristics were predefined and included several other indicators not measurable by morphology.

The types of data sources utilized in this research were intentionally limited to easily accessible, frequently updated and in some cases voluntarily contributed data, at the expense of precision and accuracy at times. These sources include GIS files available online or through request from government archives, open access mapping and street view platform Google Maps and Google Street View and social media data from

Instagram and Flickr. The reasoning behind the choice of these types of data sources are two-fold. Firstly, these sources are in rapid development in terms of accessibility and accuracy by the advance of technological developments and open data polices. For example, even though Google Street View images are not updated frequently enough to evaluate streets for different times of the year or the day, new street view image platforms have become available since the beginning of this study that can already allow for such an evaluation within the areas they cover (Nexar, 2019; Telenav, 2019), and their coverages are expanding every day. Some platforms also detect and provide the location information on streetscape objects on their maps (Mapillary, 2019). Secondly, even though not fully utilized in this research, algorithmic methods to obtain and store this data can be adapted to integrate databases in their automated aggregation, filtering and organization as well as integration into urban assessment processes. Although some of the same or similar types of data have been utilized in walkability research before (Liu & Young, 2016; Vargo et al., 2012), the comprehensive morphological analysis at neighborhood and street scale exclusively based on open data is a unique contribution of this study. It should also be noted that rather than the specific sources of the data used in this research, the replaceability of data by more accurate, accessible and faster updated versions is of significance counting on the promise of remote sensing and other data acquisition technologies' rapid advancement (Glaeser et al., 2015; Zhu et al., 2017). For the above presented reasons, development of built environment assessment methods based on these types of data is deemed to be open for innovation and faster integration with automated analysis systems.

A major concern and priority for the workflow developed in this research was that even though the assessment relied on several software and therefore could not be fully automated, each step relies on fully or partly customized algorithmic processes. These include custom Python codes run in QGIS and Rhinoceros3d software developed prior to this research by other members of the research team (J. N. Beirão et al., 2014, 2015; Sileryte, Čavić, & Beirão, 2017); Grasshopper definitions improved and extended specifically for and through this research, web-scraping codes compiled and customized using openly available Python code and code written in the statistical analysis software R. Visualizations presented in this research was done using standard QGIS commands which can easily be compiled into to custom codes operable by fewer commands. The majority of data obtained and processed through these procedures were in the format of comma separated value (CSV) files which can easily be adapted to database management systems. Thus, even though the goal of this research was not to develop a fully automated or stand-alone software for walkability analysis, the utilized algorithmic methods present the potential for further optimization, through integration with server or cloud-based database management systems. This would mean a higher level of automation, accessibility by less code-native users and constant updating of scraped data. For these reasons, the accuracy or precision of utilized data and of analysis methods were at times compromised in return for higher levels of automation and use of open data sources.

The first-time application of the 3d morphological analysis method Convex and Solid-Voids in real cases and specifically for the measuring of walkability is also considered an important contribution to the field of urban studies. While there may be a number of limitations that necessitate the further development and improvement of the model which will be addressed in detail in the following section, as a first step, this study introduces and quantitatively measures several morphological attributes of the built environment and links them with the very tangible urban issue of walkability by using the Convex and Solid-Void model. Development of this model is also extends the Space Syntax methodology by allowing for an automated 3d morphological analysis of the built environment. The 3d street-space unit Street-Void was developed and used for the first time to aggregate all measured quantitative data facilitating a practical means of evaluating several morphological attributes.

The shapes and uses of street spaces were proposed as distinguishing characteristics requiring the application of different quantitative criteria for the measuring of their walkability. Whether a street space is more street or square-like, and whether it is predominantly residential or mixed-use were found to determine the relationship of many morphological attributes with their walkability levels. More specifically, many attributes were found to be more critical for street-like and residential spaces to be more walkable, whereas square-like and commercial spaces were found to accommodate vibrant street-lives even when their attributes were comparatively less aligned with attribute behaviors determined to support walkability in established literature.

Finally, the recommendations presented as a final output of this study were structured in a way to facilitate both holistic or fragmented analysis and improvement scenarios, taking into consideration different stages of municipal interventions, specifically looking at the processes in Turkey and Portugal. In both countries, the studied neighborhood scale street attributes concern primarily the most detailed plans that are implementation plans in Turkey and Plano de Pormenor in Portugal which concern local and metropolitan municipalities. In both countries, private developers can also propose urban design plans for the immediate environment of their lots. Additionally, street network properties in the cases that they are designed from scratch concern higher level plans, subject for analysis in this thesis as well. In that case, central municipalities and governments get involved. This study addresses all these private and public stakeholders and the recommendations are organized in a step by step structure so that they can be utilized as either a complete set or in a piecemeal way, where smaller scale interventions are possible, also allowing for more rapid improvements. This was one of the main drivers behind the decision to study neighborhood and street-level morphological attributes contributing in walkability of urban environments as opposed to larger scale measures and assessment methods which are only applicable for the improvements of the built environment in larger scale regeneration projects, long term growth scenarios or in the development of new neighborhoods. The workflow at its current stage of development can be utilized to provide consulting services to the above-mentioned stakeholders. Its future versions can be utilized as a set of design support tools by third parties.

8.2 Limitations

8.2.1. Concept limitations

The introduction of the subject of this dissertation in academic environments that are less familiar with quantitative walkability assessment and computational design methods often raises questions regarding the extent of measurability of the experience of walking which is arguably highly subjective. The set of attributes utilized in this research remain rather abstract when we consider the wide range of variability in the physical capabilities and mental dispositions of pedestrians, their intentions for walking and the multitude of internal and external conditions that can affect the quality of the walking experience. Here, the concept of affordance may become useful, which explains that what is offered to the perception of the observer by the environment involves and depends on three components: the observer, the environment, and the intended purpose (Maier, Fadel, & Battisto, 2009). Within the scope of this research, these components can be defined as the persons to experience walking, the environment that would afford the conditions for walking and the purpose of the walk. Based on this concept invented by a psychologist (Gibson, 1979) we can explain that the quality of walking will be dependent on all of these three actors, and that this research is specifically concerned with the built environment, without denying the inevitable consequences of the other two.

Even when the focus is on the built environment characteristics that influence the quality of walking, its many features are considered subjectively experienced and their objective quantitative assessment can be questioned. Here it is meaningful to position this study within the context of evidence-based design and the large body of research dating back to the 80s that correlate walking behavior with the measurable qualities of the built environment through surveys and audits (Gehl, 1987; Whyte, 1980). Still, walkability is not solely dependent on morphologically evident built environment characteristics. There are several aspects of the physical environment relevant in the neighborhood or street scale that are not manifested in urban form, at least not in the detail studied within this research and thus would not be easy to detect through the methods utilized. These include but are not limited to noise, cleanliness, availability and visibility of scenery, cultural or historical meaning, functional uses that may change daily, seasonally or through longer periods of time as well as cultural and traditional appropriations. Yet this research specifically aims to support the design decisions for modifiable urban environment characteristics in municipal level urban design interventions and focus on morphological attributes as the most up-to date and objectively measurable evidence of the built environment physical conditions. Nevertheless, some of these aspects are addressed as part of the affordances which are consequences of the morphological attributes measured.

The climatic conditions, experience of which undoubtedly depend on the morphology of the built urban environment and are highly influential for walkability are not addressed within the scope of this research. A large body of literature already exists that investigate the relationship of walkability and climatic comfort and within the context of evidence-based design practices, several simulation methods allow for the testing, optimization and generation of design solutions for the most favorable climatic conditions. In addition to the climatic changes through the day and year, the temporal aspects such as the permeability of facades changing due to the opening hours of businesses, public amenities like playgrounds and parks or the varying occupancy of the sidewalk at different times of the day by stores, restaurants, bars and cafes are not directly addressed in this study. However, the characteristic of diversity based on use measured by Google Place frequencies indirectly depend on different amenities extending the daily hours that the facades and sidewalks become active. Stores, cafes, restaurants and bars activate streets beyond the popular hours of the residential streets. Nevertheless, a more fine-grained analysis taking into consideration such temporal aspects can be possible with the proposed analysis model through the 3d representation model being fed this information and analyzed in multiple states, and the use of street view imagery collected at multiple times throughout the day.

Morphology is referred to indicate a specific set of physical qualities in this thesis, regarding the built environment that are limited to not only those that are related with walkability, but also based on their measurability by the remote and semi-automated method proposed in this research. It should be noted that urban morphology, in fact, encompasses a wider range of phenomena pertaining to the relationships between the buildings, their surrounding open spaces, the lots and the streets; beyond the scales, proportions, street network attributes and existence of various streetscape elements. While many such qualities are not accounted for by the measuring method presented in this research, an initial first step is presented towards a comprehensive morphological analysis proposed to provide essential evidence for the walkability of the built environment.

It should also be underlined that the findings of the study are limited by the 4 cases studied in the two cities Istanbul and Lisbon. While they do represent diversities in the built environment that are inevitable due to being from two different countries, the two cities also have several similarities such as hilliness and active outdoor use due to mild climatic conditions and culture. Still, the model should be tested in multiple different contexts and developed accordingly to be more accurate and reliable.

8.2.2 Technical limitations

The level of morphological detail analyzed by the Convex and Solid-Void models at their current stage of development is limited such that only three types of urban limits are taken into consideration. These are the topography, buildings and planar limits which can be garden walls, construction walls, gates, hedges and operable barriers. The topography mesh is constructed using the elevation points from the topographic plans provided from the municipalities. The resolution of these plans only reflects the topographic morphology very roughly. Thus, the topography mesh analyzed is an extrapolation resulting with estimated elevation values for many points on the streets such as the entrance points of the buildings or sidewalks. The buildings and other planar limits are modeled by extruding the footprint polygons and lines respectively, thus a change in the mass of the building above the first floors of the buildings or walls are not accounted for. For the objectives of this research, this lack of detail is acceptable as it does not compromise the measures of the indicators utilized. For example, the topography is only utilized for calculating the slope on the streets and visibility of the skyline, and the buildings and walls are only considered as physical boundaries on the ground level, as also supported by similar uses in literature (Beirão & Koltsova, 2015; Ewing & Handy, 2009; Gehl, 1987; Van Nes, 2011). However, morphology of urban spaces can be far more intricate with spaces such as building galleries, underpasses or arcades with one or both sides open to the street; they may have non-uniform boundary heights, can consist of various materials that may limit physical access but allow for visual access; or have surface treatments that ease or impede walking, reflect or absorb light and thus affect the walking experience that the current model cannot account for. The extent of detail to be measured by the morphological analysis model utilized in the current research is aimed to be improved in parallel with the level of detail of the data that can be obtained openly and freely in formats that allow for the automated generation of urban models. The Convex and Solid-Void models developed by the Design Computing Group at the University of Lisbon already has a module in the stage of development that allows for the input of horizontal limits able to generate gallery, underpass and arcade spaces (Sileryte et al., 2017).

The street view analysis method utilized in this model was dependent on the availability and resolution of the Google Street View images captured in the studied areas as well as the accuracy of the image recognition software algorithm utilized. This meant that the streets through which the street view surveying vehicles could not enter were not assessed and elements that the image processing algorithm could not identify were not accounted for in the analysis. Yet the levels of detail captured by open source street view providers increase every day and there are several studies dedicated to improve image recognition algorithms to better identify built environment elements (De Nadai et al., 2016; Naik et al., 2014, 2016).

The aim of this research was to optimize and semi-automate the complete process of assessment starting from the generation of the 3d model to be analyzed. Hence the current model was deemed sufficient to assess the built environment in a level of articulation that could be generated with the most recently available and accurate morphological data of the areas that were analyzed. The indicators measured also captured more detail than has been analyzed in previous walkability studies specifically concerned with urban morphology that also aimed for automated methods. As remote sensing technologies progress, the 3d models generated will be higher in resolution and the delineation processes of the built environment elements will become more effective and the level of detail to be assessed will increase. Nevertheless, the abstraction levels of the models always require to be determined judging on the processing costs and benefits provided by the detail.

One aspect of the structure of this research that may raise questions is that the indicators identified and reduced into a final set were not validated through statistical correlations with walking behavior. However, in line with the principle to eliminate surveys and utilize open access data in the evaluation workflow utilized, resource intensive audits were avoided in the validation process as well. Instead, geo-located social media data along with people counts on Google Street View images were utilized as indicators of street activity and were tested for correlation with built environment characteristics. Even though they were not found to perform as consistent outcome variables to represent walking behavior for predictive analysis, where data was available, they were helpful in comparing activity in groups of street spaces. Additionally, unsupervised and supervised machine learning methods were utilized to group indicators and identify most representative ones.

It should also be acknowledged that the relationship of many attributes studied in this research with walkability may not be linear, which hasn't been addressed within the scope and through the samples studied in this dissertation. One example can be the way we consider 3d enclosure of street spaces to be positively correlated with walkability. Measured by the proportion of building heights to street widths and the proportion of the visible sky, the behavior of this characteristic may begin to change or be affected by additional factors in contexts where scale related built environment attributes are in more extreme ranges. This could very possibly be the case for a neighborhood like midtown Manhattan in New York where the skyscraper heights could result in comparatively high enclosure values even for very wide streets that may in fact not feel as enclosed or contrary to expectation, very low skyview values may negatively impact perceived walkability. This issue should be addressed through future work by the multiplication of contexts studied and development of statistical methods applied.

8.3 Future Work

In its current state, it is anticipated that the contributions of the thesis benefit decision makers through the recommendations and by the use of the walkability analysis workflow presented. This analysis can at this stage be provided in the form of consulting services. In future studies, the workflow is to be further developed and streamlined into a tool or a set of tools to be utilized directly by designers and decision-making authorities. Moreover, the proposed methodology combining the 3d-model and street-view image-based analysis can act as a first step in establishing a more comprehensive and detailed morphology-based urban analysis framework applicable to different concepts in addition to walkability. Urban vulnerabilities or real estate values are examples to possible subjects for study. Accessibility for people of different age groups and physical conditions can be studied; changes in conditions through time such as varying accessibility or climatic effects through daily or seasonal cycles can be focused on; or urban transformation effects such as growth or gentrification may be further researched.

The workflow can be improved through further development and better integration of image recognition and 3d-model representation capacities, incorporating LIDAR and satellite imagery data and its analysis for a more extensive and higher resolution evaluation applicable to larger areas of study, as well as being integrated with databases for the automated aggregation and management of the utilized data. Also, the output of the evaluation can be extended and linked with generative design methods. Such a conceptual model has been defined in Chapter 2 (Figure 2.1).

The Convex and Solid-Void models utilized to analyze 3d morphology is also subject for future research. It is to be developed not only to overcome the limitations mentioned in the previous section, but also to facilitate additional levels of evaluation, such as network-topological analysis as well as to allow for more detailed 3d morphological analysis in street-level to take into consideration material properties of surfaces and street elements like furniture and fixtures. A preliminary concept towards a finer grained morphological analysis using the Convex and Solid-Void model titled "Fragmented Voids" has already been proposed by Čavić (2018) in her dissertation.

Among the improvements to address the limitations mentioned above, working with a larger and more complete dataset that includes a more reliable walkability indicator variable to use for predictive model building should be the first step. Additionally, attributes found to show inconsistencies with literature should be thoroughly tested, if necessary, by carrying out individualized studies for each of them. Depending on the availability of data, temporal changes should be addressed by creating different states for the 3d models worked with which should be analyzed. Doing this would not only strengthen the analysis workflow, the results may challenge literature on how the built environment affects walkability in general and in different contexts and conditions.

To increase the size and diversity of the dataset worked with, contexts with more extreme conditions, covering larger areas and with finer-grained 3d information available for more detailed morphological analysis are among the future work envisioned. Neighborhoods within the island of Manhattan present good possible cases in terms of all these aspects having high level of detailed data openly available and a wide range of physical built environment characteristics. Another interesting type of context to apply the analysis workflow is post-conflict urban environments which are usually harder to access to analyze on site and find data about as well as being in rapid transformation. For these reasons they are especially suitable for the remote analysis method proposed in this study. Syrian cities that have gone through high levels of destruction in the Syrian civil war some of which have recently been analyzed by satellite imagery (REACH, 2019) are examples to contexts that are of interest for future study.

8.4 Summary

For ease of comprehension the conclusions are itemized below.

- This research presents a semi-automated workflow based on 3d morphology and streetscape attributes in the street scale, utilizing remotely and openly accessible urban data obtained from GIS inventories, social media and mapping platforms, utilizing web-scraping and image recognition analysis techniques.
- Existing walkability related built environment attributes are analyzed through a literature study and re-grouped under morphological characteristics. A large list of measurable morphological attributes is tested through case studies in 4 neighborhoods from 2 cities and reduced to a smaller number of reliably measurable attributes with the proposed model.
- One contribution is considered to be the use of a remotely applicable micro-scale 3d morphological analysis of walkability-related characteristics that reduces the cost and time requirements of surveys done for urban analysis also making it possible to assess inaccessible sites where doing surveys is not practical.
- The study is a first-time application of the 3d morphological representation method Convex and Solid-Voids to the analysis of an urban problem, in which the relationship of quantitative street attribute measures with tangible, observed neighborhood characteristics are clearly identified, even though their relationship with walkability should be better established through further quantitative analysis.
- Descriptive analysis results were used to provide recommendations for street-scale improvements in design and planning level interventions with direct-physical and indirect-perceptual impact. These recommendations are deemed applicable to urban planning or improvement scenarios conducted by metropolitan or local municipalities and private entities for the contexts of Istanbul and Lisbon while the administrative capacity of local and central authorities should be taken into consideration when studying different contexts.

- Limitations of the study include not accounting for universal accessibility issues for disadvantaged pedestrian groups like the disabled, kids and the elderly; the limited nature of cases studied; exclusion of climatic comfort related consequences of morphology and temporal changes in street scape due to daily, seasonal or longer period cycles influencing physical and use conditions.
- Technical limitations that are acknowledged and seen as subject for future work include the lack of validation data representing actual walking behavior and some insufficiencies in the social media and people count data utilized instead, as well as inaccuracies in both the 3d morphological and street view analysis in the cases studied, again resulting from the imprecision of available urban information in the studied scale.
- The methodology is proposed to be improved through future work by utilizing more comprehensive data, the addition of new contexts for case studies and fine tuning of the analyses involved. The results are to be tested through a more accurate validating variable then the utilized social media and street view-based people counts, after which inconsistencies should be addressed one by one for each attribute.
- As part of future work, the structure of the workflow combining GIS, 3d modeling and programming environments is envisioned to be integrated into more robust analysis and design processes into which up-to-date urban data can be fed through databases and results can be used to generate flexible design solutions.

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APPENDICES

APPENDIX A: Walkability attribute table (in CD-Rom).

APPENDIX B: Neighborhood selection stage analyses maps (in CD-Rom).

APPENDIX C: Convex and Solid-Void attribute maps (in CD-Rom).

APPENDIX D: Building attribute maps (in CD-Rom).

APPENDIX E: Aggregated Space Syntax attribute maps (in CD-Rom).

APPENDIX F: Aggregated steet view attribute maps (in CD-Rom).

APPENDIX G: Street view point attribute maps (in CD-Rom).

APPENDIX H: Activity attribute maps (in CD-Rom).

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PUBLICATIONS/PRESENTATIONS ON THE THESIS

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APPENDICES

APPENDIX A: Walkability attribute table.

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APPENDIX H: Activity attribute maps

APPENDIX A

Table A.1 : Walkability related characteristics and attributes.

Characteristic	Attribute	How is it measured traditionally?	Method proposed
Density		Number of residential units, number of non-dwelling units, residential floor area, total floor area, building footprint area or population is divided by unit area of analysis.	
	Building area density	Total building footprint area is divided by unit area or length of analysis.	Convex and Solid-Void models, based on building footprint area per unit length and area of street space.
	Floor area density	Total of building floor areas is divided by unit area or length of analysis.	Convex and Solid-Void models, based on building footprint areas and number of floors per unit length and area of street space.
	Density of amenities per unit area	Number of varying or specific types of amenities, amenities per network distance, travel time distance, or buffer area.	Google maps places and Convex and Solid-Void model units
Diversity		Number or floor area of various amenities, their proportions to residential unit numbers or total floor areas, number of shops, recreational and other amenities within unit area of study. Network, point distance or travel time distance to closest amenities. Measure also commonly referred as land-use or entropy measure.	

Characteristic	Attribute	How is it measured traditionally?	Method proposed
	Number of building or wall facades per unit length	Number of building facades per 100m have been used for measuring complexity (Ewing & Handy, 2009) and perceived safety of the built environment (Harvey et al., 2015)	Convex and Solid-Void models, based on number of building and urban limit faces per unit length of street space.
	Variation in building heights	Not a previously utilized measure of diversity	Convex and Solid-Void models, based on number of floors for each building
	Variation in building footprint areas surrounding a unit area	Not a previously utilized measure of diversity	Convex and Solid-Void models
	Variation in building floor areas surrounding a unit area	Not a previously utilized measure of diversity	Convex and Solid-Void models
	Variation in street widths	Not a previously utilized measure of diversity	Convex and Solid-Void models
	Variation in footprint shapes of unit street spaces.	Not a previously utilized measure of diversity	Convex and Solid-Void models, using squareness and compactness (see Table 4.2)
	Variation in elevation within a unit street space.	Not a previously utilized measure of diversity	Convex and Solid-Void models
	Variation in percentage of visible sky within a unit street space.	Not a previously utilized measure of diversity	Convex and Solid-Void models

Characteristic	Attribute	How is it measured traditionally?	Method proposed
	Density of amenities per unit area	Number of varying or specific types of amenities, amenities within a network distance, travel time distance, or buffer area.	Google maps places and Convex and Solid-Void model units
	Diversity of land-use and amenities	Number of varying or specific types of amenities, amenities within a network distance, travel time distance, or buffer area.	Number of types of amenities per unit area (This measure was omitted in the method due to insufficient variation across neighborhoods.)
Connectedness		Several different indicators are utilized to account for connectedness (connectivity) of street network in walkability studies (Ewing & Cervero, 2010). It is sometimes referred to with different terminology (Pikora et al., 2002).	
	Density of walkable paths per street space	Street density is a commonly used measure, including in wider scope studies (UN Habitat, 2013). Total segment length is divided by total area analyzed.	Convex and Solid-Void models, by total segment length divided by street space area
	Node count	The number of all street segments passed through in the routes from a street segment to all others in the network, measured using Space Syntax methods/software.	Space syntax measures aggregated within Convex Solid-Void units
	Connectivity (Space Syntax indicator)	Number of street segments immediately connected to a street segment, measured using Space Syntax methods/software	Space Syntax software results aggregated within Convex Solid-Void units

Characteristic	Attribute	How is it measured traditionally?	Method proposed
	Angular Connectivity	Cumulative angle of all segments connecting to a street segment, measured using Space Syntax methods/software	Space Syntax software results aggregated within Convex Solid-Void units
	Total depth	The total of all topological depths from any street segment to all other street segments, measured using Space Syntax methods/software	Space Syntax software results aggregated within Convex Solid-Void units
	Choice	How likely a street segment is to be used within all the shortest routes connecting all street segments to all street segments, within the given radius, measured using Space Syntax methods/software	Space Syntax software results aggregated within Convex Solid-Void units
	Integration	The normalized distance from any street segment to all other street segments in the network; how close each segment is to all the other segments, measured using Space Syntax methods/software.	Space syntax software results aggregated within Convex Solid-Void units
(Human) Scale		Human scale is used as a walkability measure to account for the sizes of street features and weather elements like street furniture that relate to the body's scale exist (Ewing & Handy, 2009)	
	Street space footprint area	Not a common measure of human scale	Convex and Solid-Void models
	Street segment length	Commonly used as part of Space Syntax measures, corresponds to block length also used in walkability studies.	Convex and Solid-Void models and street network
	Average street space width throughout the street segment	Although not commonly used for human scale measures, utilized in walkability studies.	Convex and Solid-Void models

Characteristic	Attribute	How is it measured traditionally?	Method proposed
	Average height of buildings and walls throughout a street segment	Building heights are used in walkability measures, as part of human scale measures (Ewing & Handy, 2009)	Convex and Solid-Void models
	Number of building and wall facades per unit length	Not a common measure of human scale	Convex and Solid-Void models, based on number of building and urban limit faces per unit length of street space.
	Average width of building and wall façades surrounding a street segment	Not a common measure of human scale	Convex and Solid-Void models
	Average number of floors of buildings surrounding a street segment	Not a common measure of human scale	Convex and Solid-Void models
	Average footprint area of buildings surrounding a street segment	Not a common measure of human scale	Convex and Solid-Void models
	Average floor area of buildings surrounding a street segment	Not a common measure of human scale	Convex and Solid-Void models
	Average number of street sides where street furniture was identified throughout a street segment length	Number of instances where street furniture (Ewing & Handy, 2009; Park, Choi, & Lee, 2017) or outdoor dining (Ewing & Handy, 2009) was identified per street length have been used as a measure. On-site surveys were utilized to collect data.	Google Street View images analyzed with Clarifai prediction API, general model
Complexity		Complexity is used as a walkability measure concerning building and other streetscape elements that improve how interesting and attractive a street is, accounting for frequency of building facades, variations in color and shape as well as streetscape elements. (Ewing & Handy, 2009)	

Characteristic	Attribute	How is it measured traditionally?	Method proposed
	Number of building or wall facades per unit length	Number of building facades per 100m have been used for measuring complexity (Ewing & Handy, 2009) and perceived safety of the built environment (Harvey et al., 2015)	Convex and Solid-Void models, based on number of building and urban limit faces per unit length of street space.
	Building density	Total number of buildings is divided by the length of street unit area of analysis.	Convex and Solid-Void models, based on number of neighboring buildings per unit length of street space.
	Density of walkable paths per street space	Street density is a commonly used measure, including in wider scope studies (UN Habitat, 2013). Total segment length is divided by total area analyzed.	Convex and Solid-Void models, by total segment length divided by street space area
	Average façade areas of buildings and walls surrounding a street segment	Not a common measure of human scale	Convex and Solid-Void models
	Average width of building and wall façades surrounding a street segment	Not a common measure of human scale	Convex and Solid-Void models
	Average number of street sides where greenery was identified throughout a street segment length	Number of instances where landscape elements were identified per street length was used as a measure of imageability (Ewing & Handy, 2009). Trees and their canopy sizes are accounted for as positive contributors to walkability in many studies (Harvey et al., 2015; Pikora et al., 2002) On-site surveys were utilized to collect data.	Google Street View images analyzed with Clarifai prediction API, general model
	Average number of street sides where street furniture was identified throughout a street segment length	Number of instances where street furniture (Ewing & Handy, 2009; Park et al., 2017) or outdoor dining (Ewing & Handy, 2009) was identified per street length have been used as a measure. On-site surveys were utilized to collect data.	Google Street View images analyzed with Clarifai prediction API, general model

Characteristic	Attribute	How is it measured traditionally?	Method proposed
	Average number of street sides where commercial activity was identified throughout a street segment length	Not a common measure of human scale	Google Street View images analyzed with Clarifai prediction API, general model
	Average number of street sides where motor transit vehicles were identified throughout a street segment length, as a negative contributor.	Not a common measure of human scale	Google Street View images analyzed with Clarifai prediction API, general model
	Number of amenities per street segment length	Number of instances where buildings with identifiers and active uses were identified is used as part of imageability and transparency measures respectively (Ewing & Handy, 2009). On-site surveys were utilized to collect data.	Google Maps API
Enclosure			
	Proportion of average building, wall or other urban limit height to average street width.	Harvey et al. (2015) as well as several other studies utilize this measure as part of enclosure measures for walkability.	Convex and Solid-Void models
	Percentage of visible sky	This indicator have been used as part of enclosure measures. (Ewing & Clemente, 2013; Ewing & Handy, 2009) On-site surveys were utilized to collect data.	Convex and Solid-Void models
	Average of height to width ratio of building and wall facades surrounding a street segment space.	Not a common measure in walkability studies.	Convex and Solid-Void models
	Proportion of total façade widths of buildings and walls to perimeter of unit street space.	Proportion of street wall have been used as part of enclosure measures (Ewing & Handy, 2009). On-site surveys were utilized to collect data.	Convex and Solid-Void models

Characteristic	Attribute	How is it measured traditionally?	Method proposed
Shape	Footprint shape of a unit street space, distinguishing between wider spaces such as plazas and narrower spaces such as streets and passageways. Also, the level of articulation of facades constituting the street boundaries are identified.	Not a common measure in walkability studies.	
	Compactness of unit street space: the ratio between perimeter of the street space unit and perimeter of a circle of the same area	Not a common measure in walkability studies.	Convex and Solid-Void models.
	Squareness of unit street space: the ratio between area of the unit street space and area of its smallest bounding square	Not a common measure in walkability studies.	Convex and Solid-Void models.
	Perimeter of street space divided by the footprint area of it.	Not a common measure in walkability studies.	Convex and Solid-Void models.
Inclination			
	Average slope of all walkable paths within a street segment space	Used by Özbil et al. (2015) as part of walkability analysis and Vale et al. (2016) refer to studies that take into account slope for walkability and bikeability.	Convex and Solid-Void models.
	Maximum change in elevation throughout the street segment space, divided by street segment length. Differs from slope accounting for the whole footprint of street space rather than walkable paths. May indicate view/scenery.	Not a common measure in walkability studies.	Convex and Solid-Void models.

Characteristic	Attribute	How is it measured traditionally?	Method proposed
Permeability/ Transparency		Based on the “Eyes on the Street” theory of Jacobs (1963), and the idea that more entrances mean more street activity, this indicator is sometimes used in walkability studies.	
	Average number of street sides where doors or windows were identified throughout a street segment length	Number of windows have been used as part of transparency measure (Ewing & Handy, 2009), building entrances were linked to street liveliness by Beirão & Koltsova (2015). On-site surveys are commonly utilized to collect data.	Google Street View images analyzed with Clarifai prediction API, general model
Infrastructure quality (and Maintenance)		Several indicators are utilized in walkability studies that are referred to or can be referred to as infrastructure quality. Sidewalks, street furniture, transit stops, lighting, traffic calming measures, street trees are some of the elements accounting for this indicator.	
	Sidewalks: Average number of street sides where a sidewalk was identified throughout a street segment length	Existence of sidewalks and sidewalk quality have been utilized as a measure in several walkability studies. Data is commonly collected on-site but many attempts to automate the process are underway (Frackelton et al., 2013).	Google Street View images analyzed with Clarifai prediction API, general model
	Green: Average number of street sides where trees, landscape, a park or environment were identified throughout a street segment length	Visibility of landscape elements have been utilized in studies (Ewing & Handy, 2009) as well as number (Neckerman et al., 2009), canopy size (Harvey et al., 2015) and shading capacities of trees. Data was gathered on-site or through already available census-tract data sets.	Google Street View images analyzed with Clarifai prediction API, general model
	Commerce: Average number of street sides where shopping, commerce or businesses were identified throughout a street segment length	Numbers and square meters of commercial amenities have been utilized in walkability measures, commonly as part of land use mix or “entropy” indicators based on proportions with square meters of residential and other uses.	Google Street View images analyzed with Clarifai prediction API, general model

Characteristic	Attribute	How is it measured traditionally?	Method proposed
	Street Furniture: Average number of street sides where chairs, benches or other furniture were identified throughout a street segment length	Number of instances where street furniture (Ewing & Handy, 2009; Park et al., 2017) or outdoor dining (Ewing & Handy, 2009) was identified per street length have been used as a measure. On-site surveys were utilized to collect data.	Google Street View images analyzed with Clarifai prediction API, general model
	Motor Transit: Average number of street sides where cars, vehicles or traffic were identified throughout a street segment length	Traffic volume and noise as well as safety from traffic is used by studies as a negative indicator for walkability (Ewing & Cervero, 2001; Vale et al., 2016).	Google Street View images analyzed with Clarifai prediction API, general model
	Negative: Average number of street sides where abandonment, demolition or calamity were identified throughout a street segment length	Abandoned buildings (Blečić, Cecchini, Congiu, Fancello, & Trunfio, 2015; S. Lee & Talen, 2014) or inversely the buildings in active use (Ewing & Handy, 2009), as well as other street disorders (Kelly, Schootman, Baker, Barnidge, & Lemes, 2007) are accounted for in Walkability measures. Data was collected by on-site audits or manually assessing Google Street View images.	Google Street View images analyzed with Clarifai prediction API, general model

APPENDIX B

Figure B.1 : Istanbul neighborhood and case study limits.

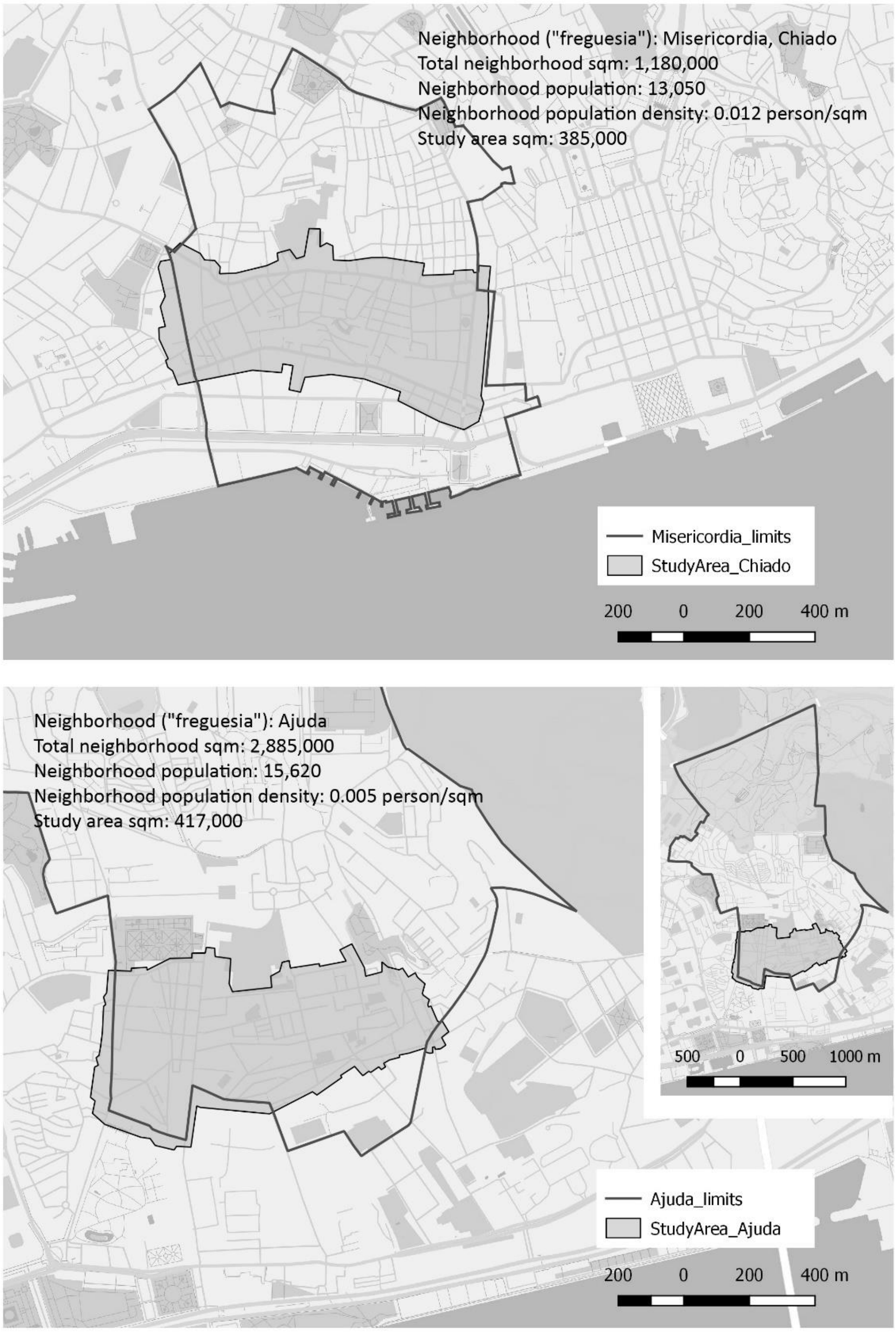
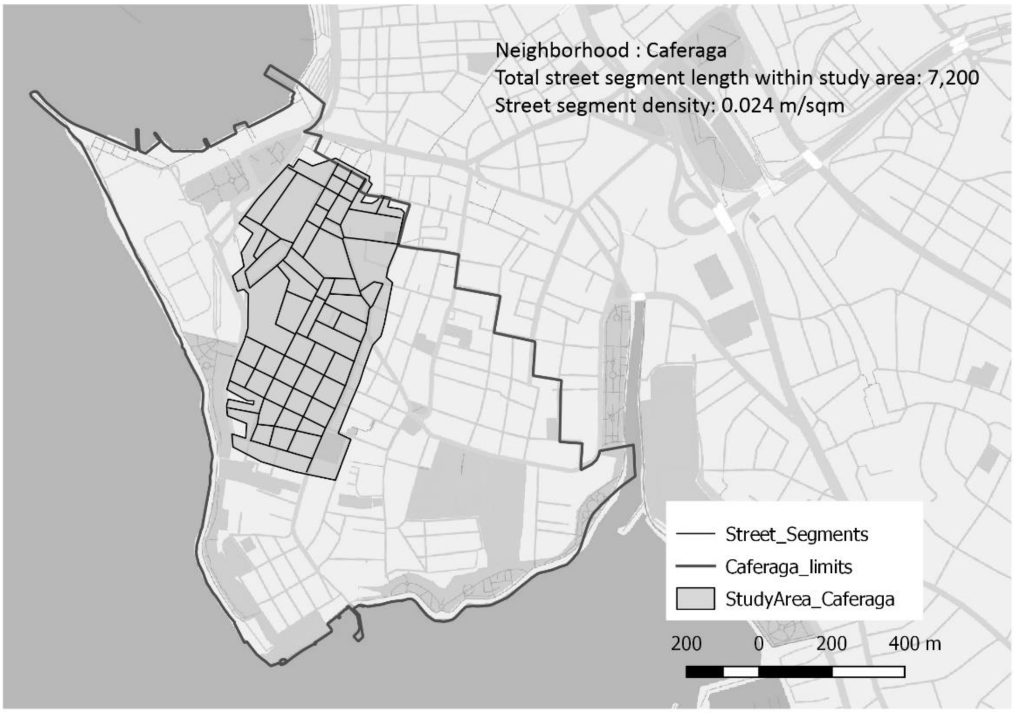


Figure B.2 : Lisbon neighborhood and case study limits.



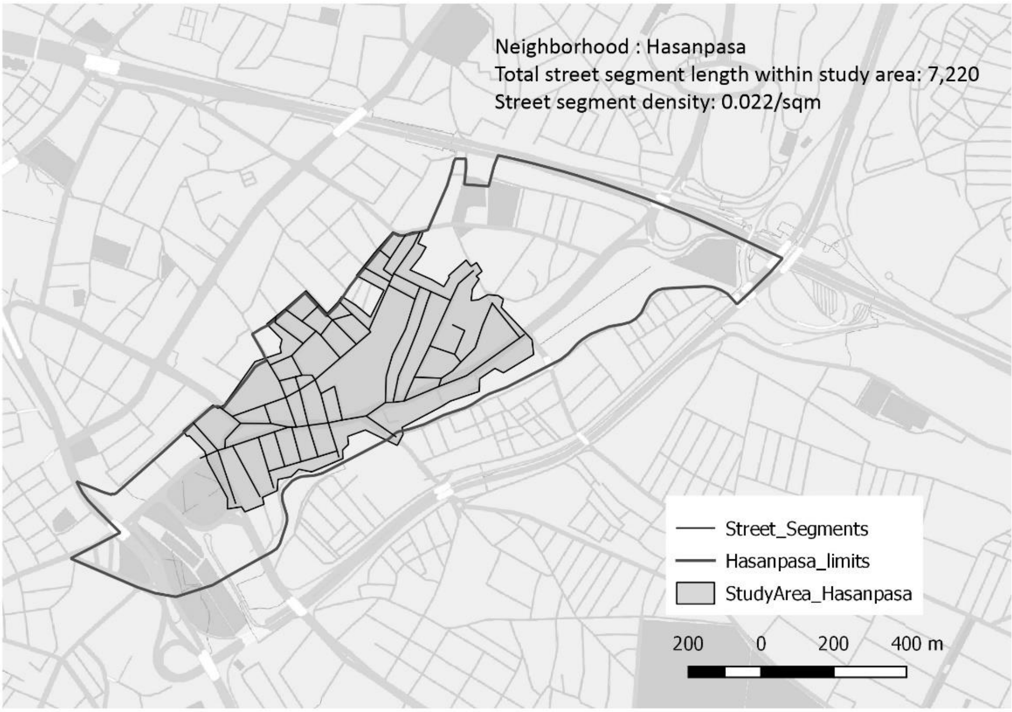
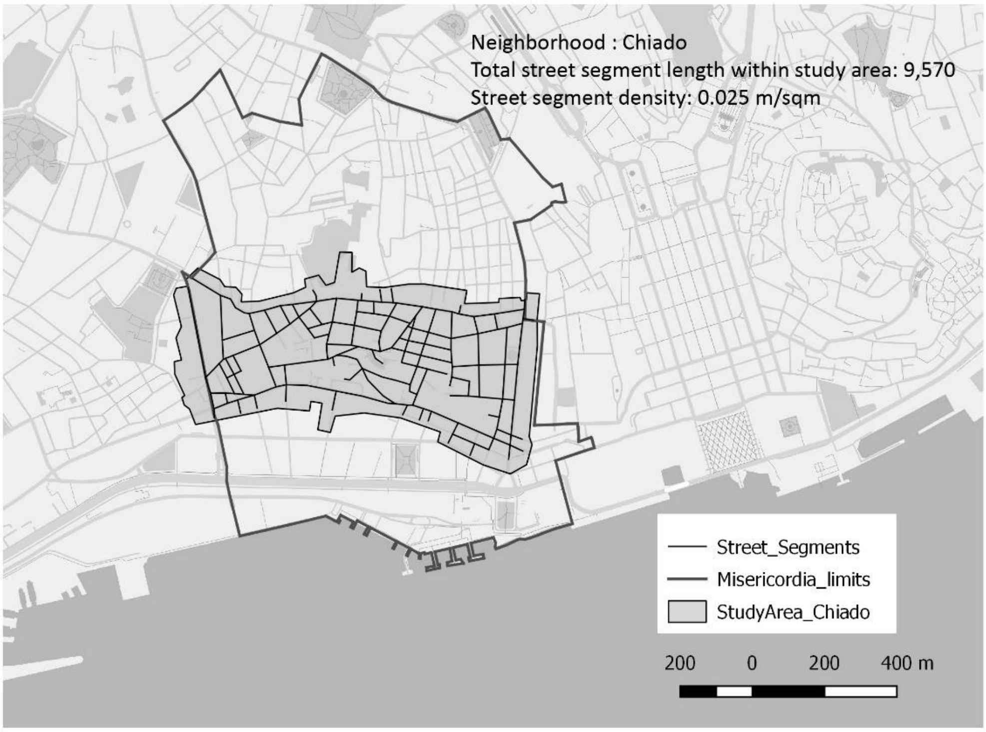


Figure B.3 : Istanbul street segments.



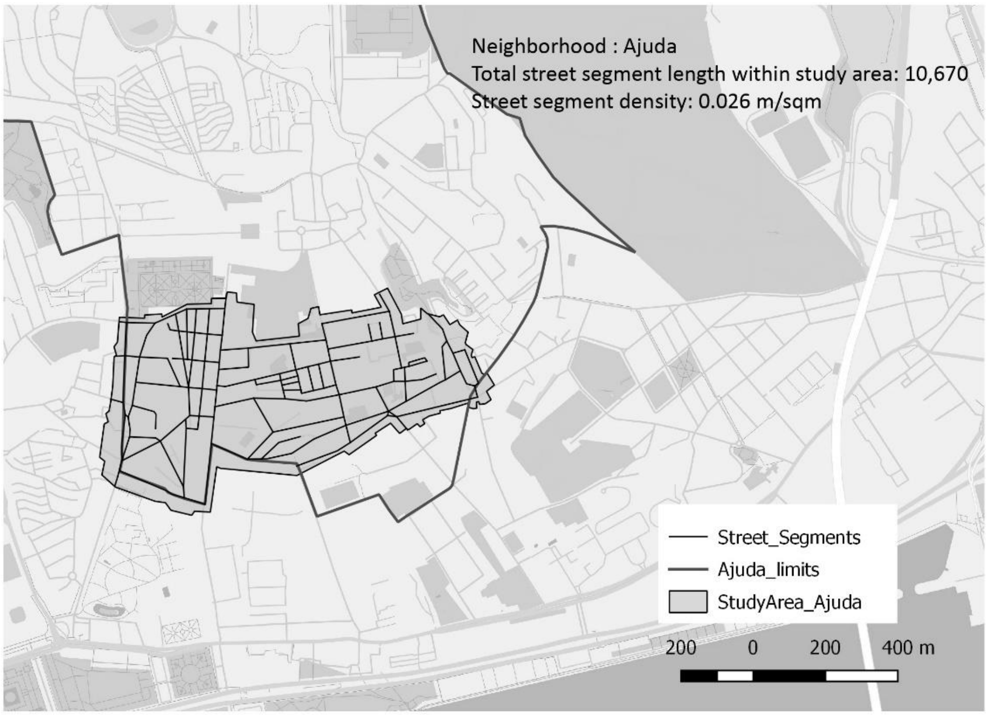


Figure B.4 : Lisbon street segments.

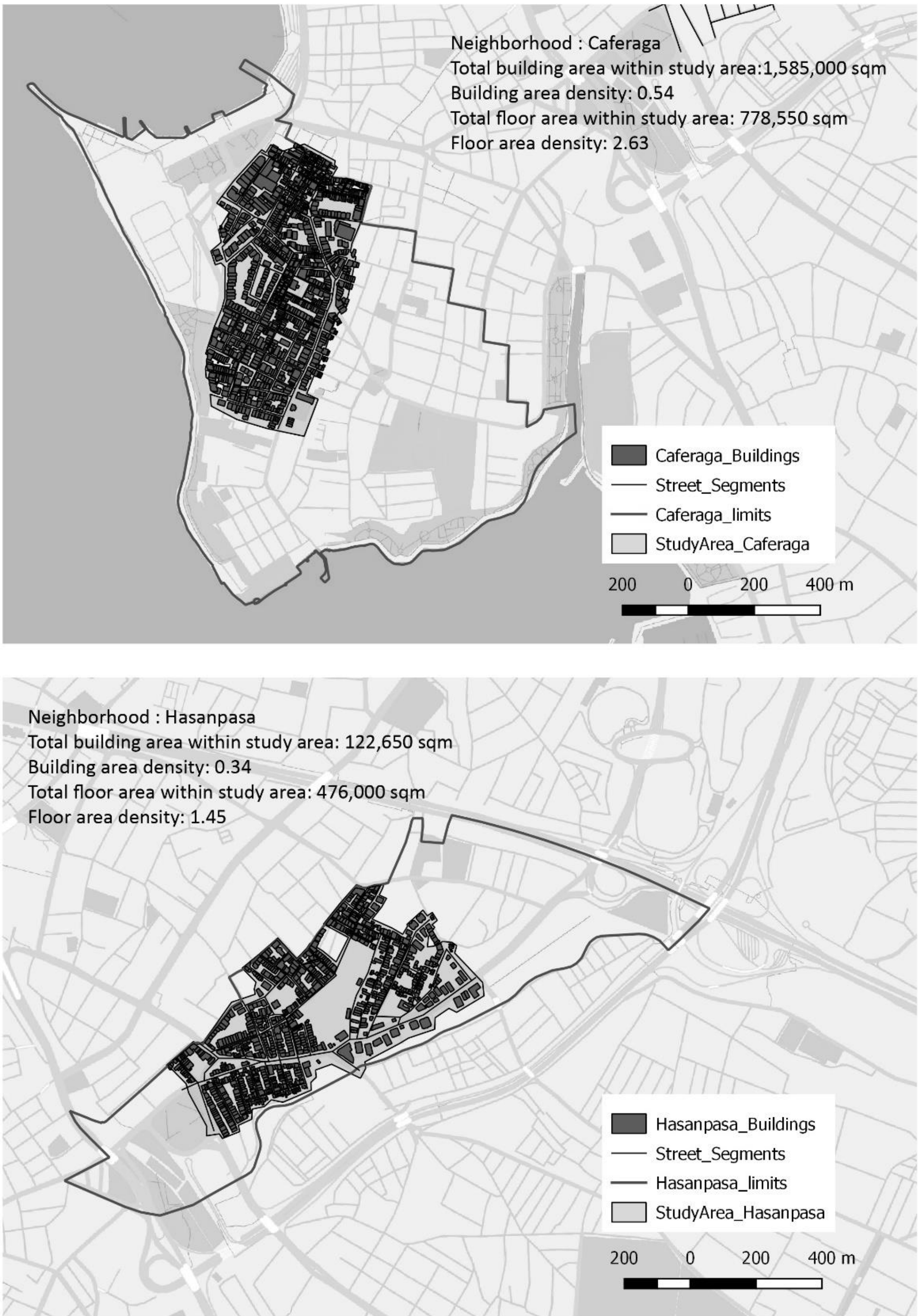


Figure B.5 : Istanbul buildings.

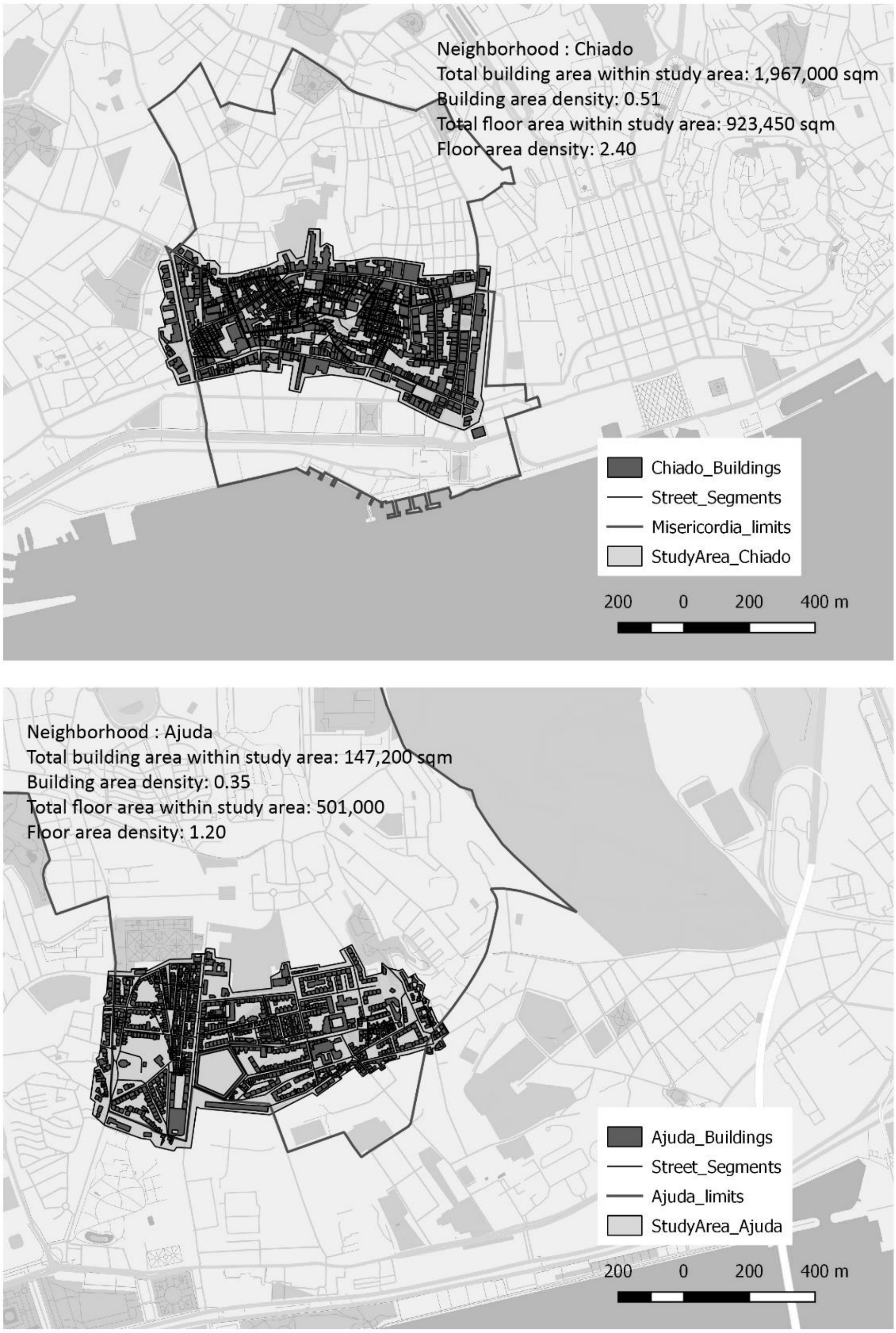
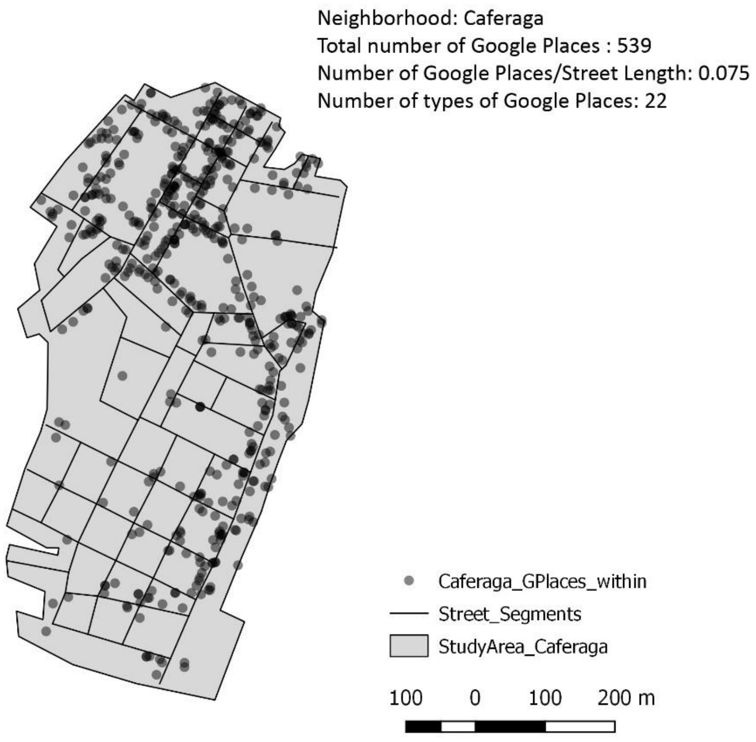


Figure B.6 : Lisbon buildings.



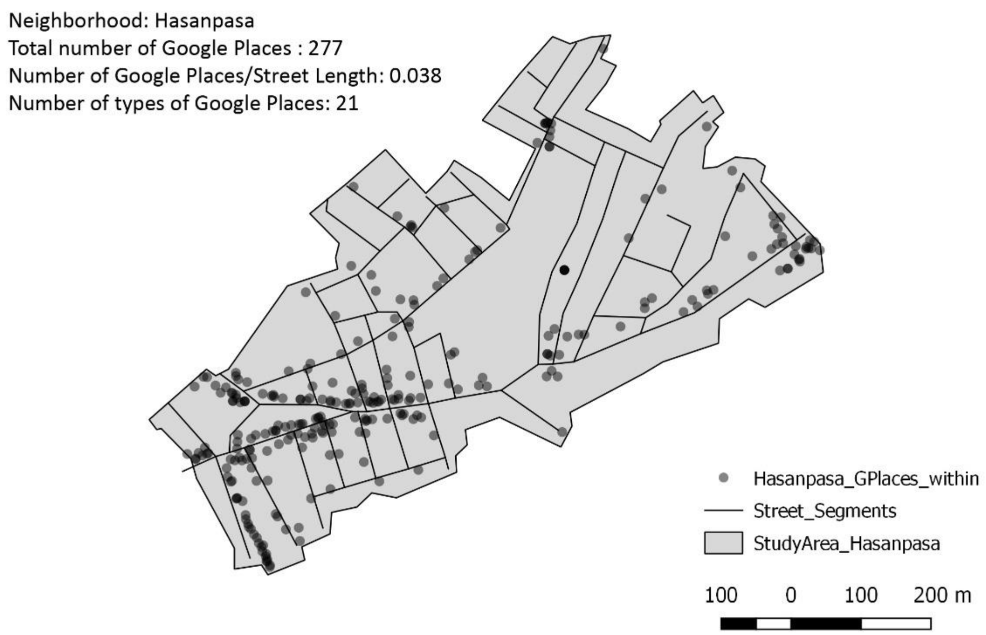
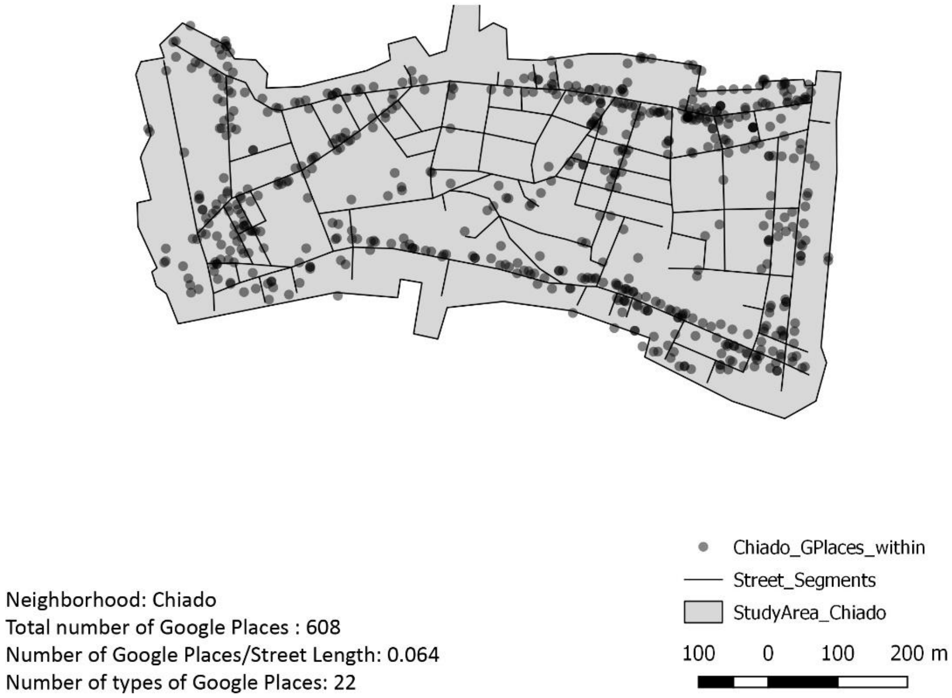


Figure B.7 : Istanbul Google Place locations.



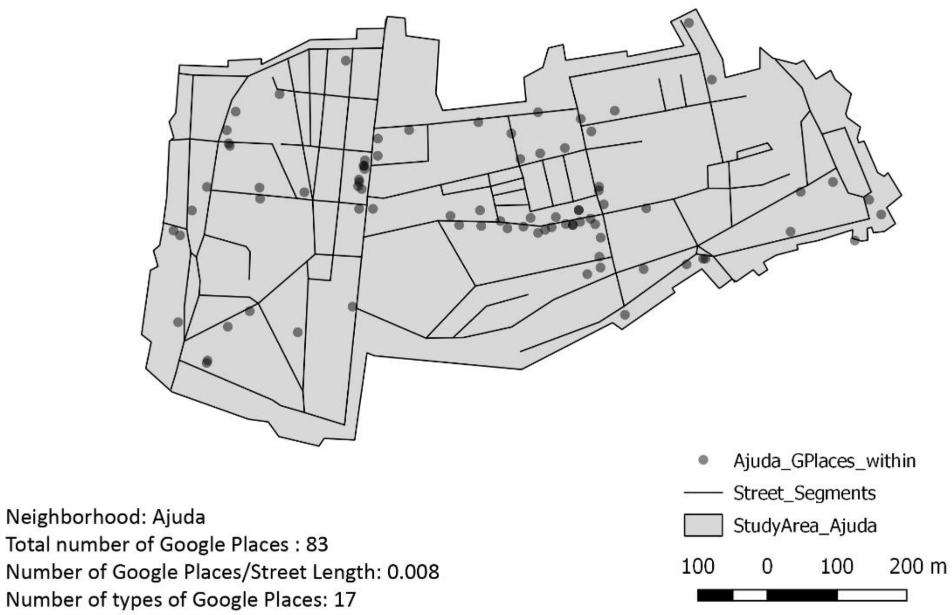
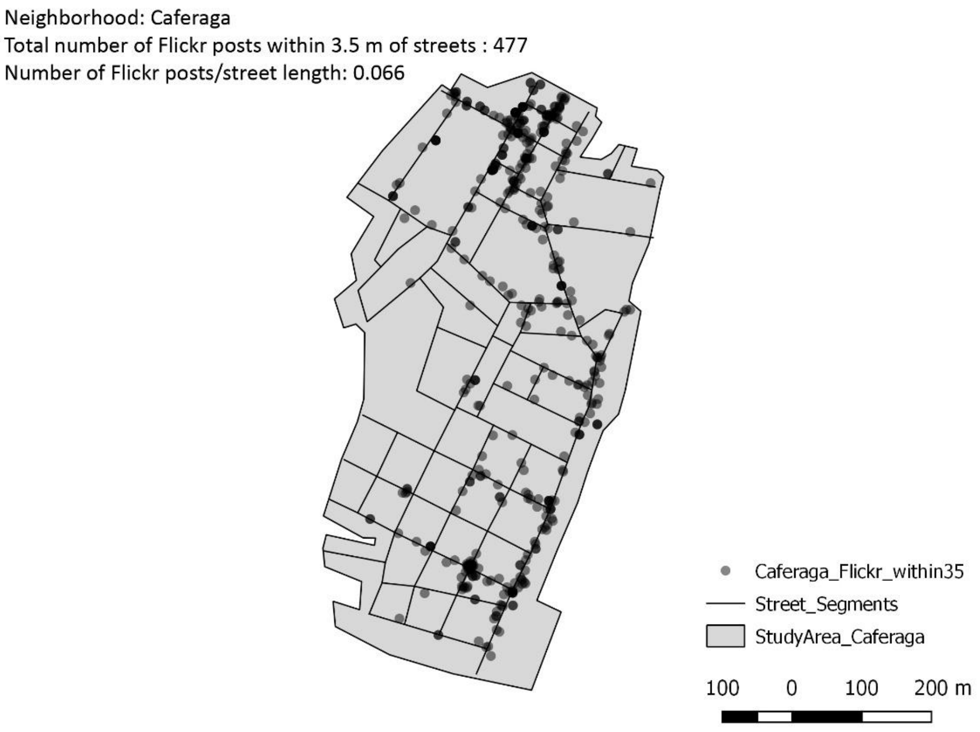


Figure B.8 : Lisbon Google Place locations.



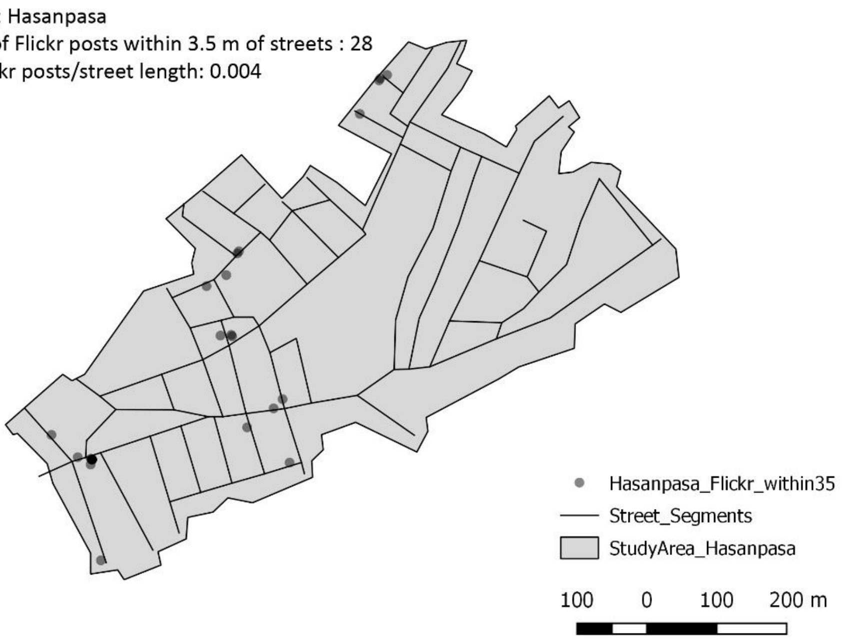


Figure B.9 : Istanbul Flickr posts.

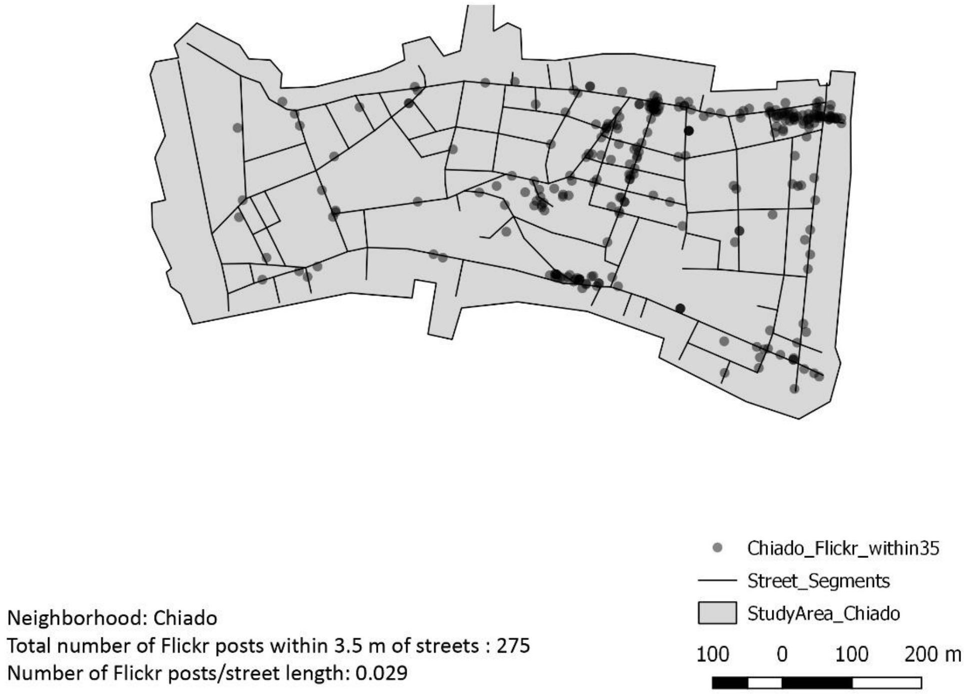
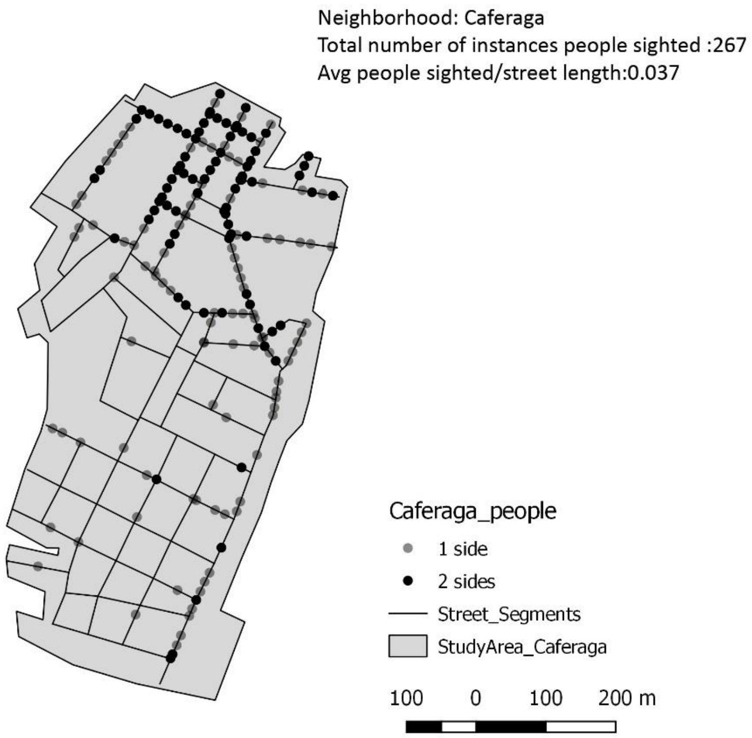


Figure B.10 : Lisbon Flickr posts.



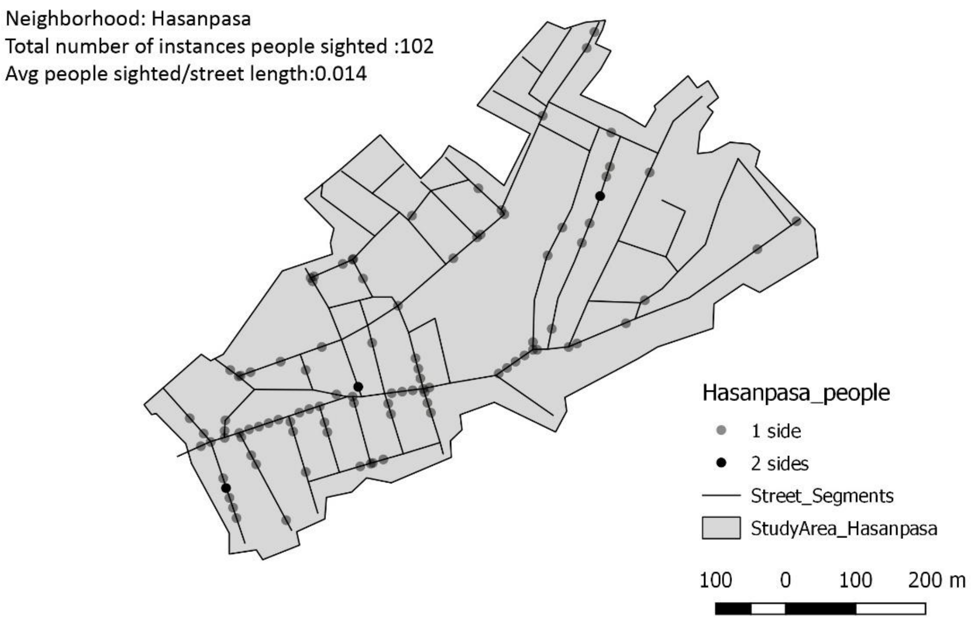


Figure B.11 : Istanbul street sides with people.

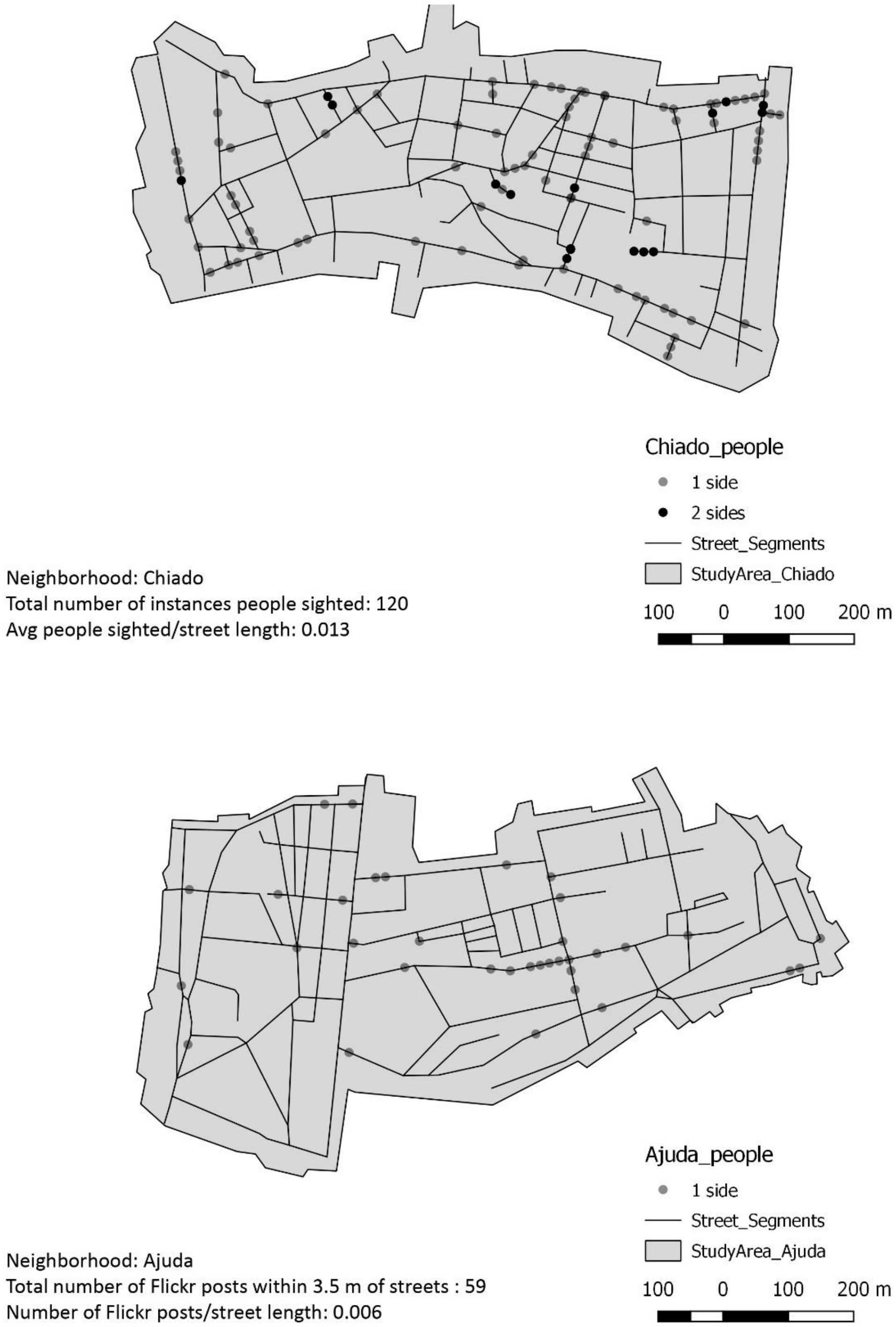


Figure B.12 : Lisbon street sides with people.

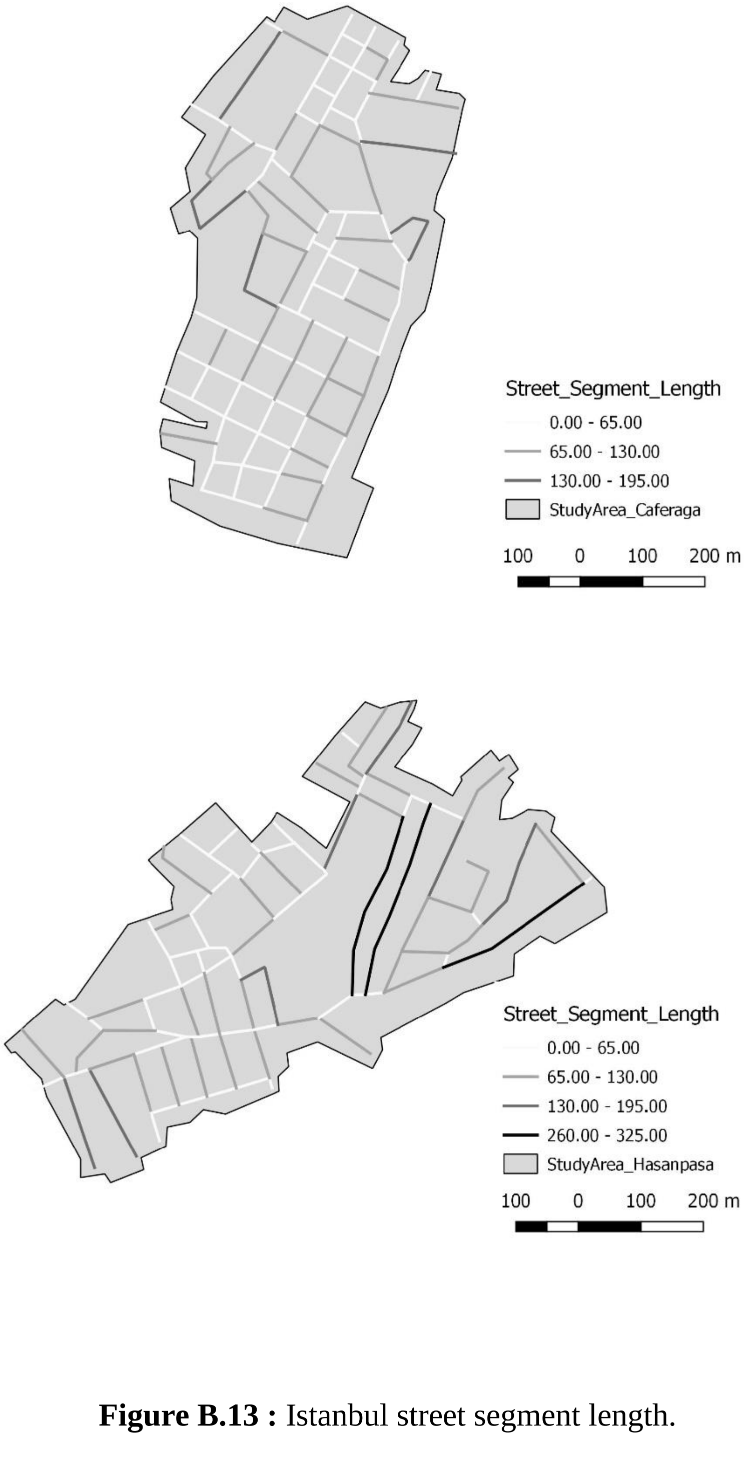
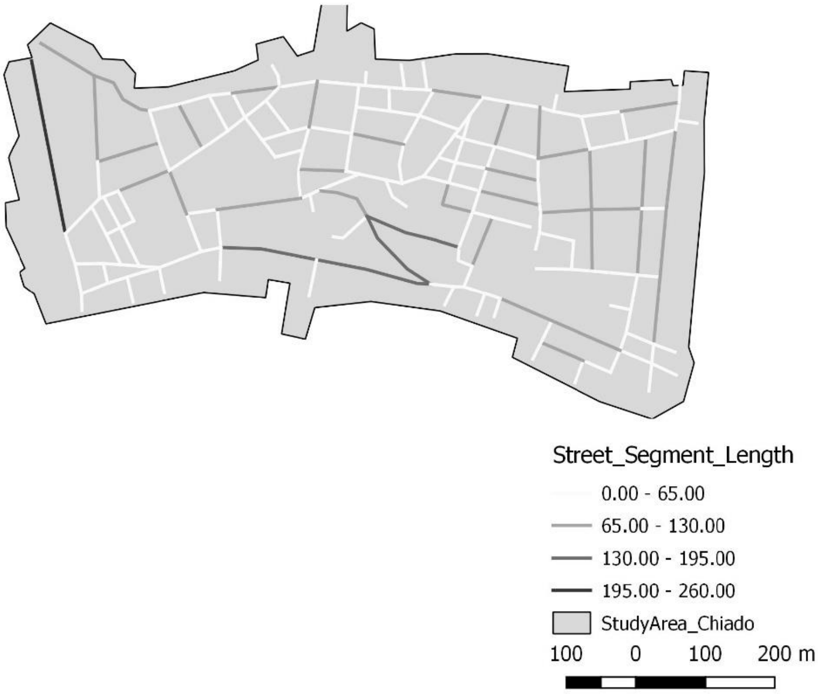


Figure B.13 : Istanbul street segment length.



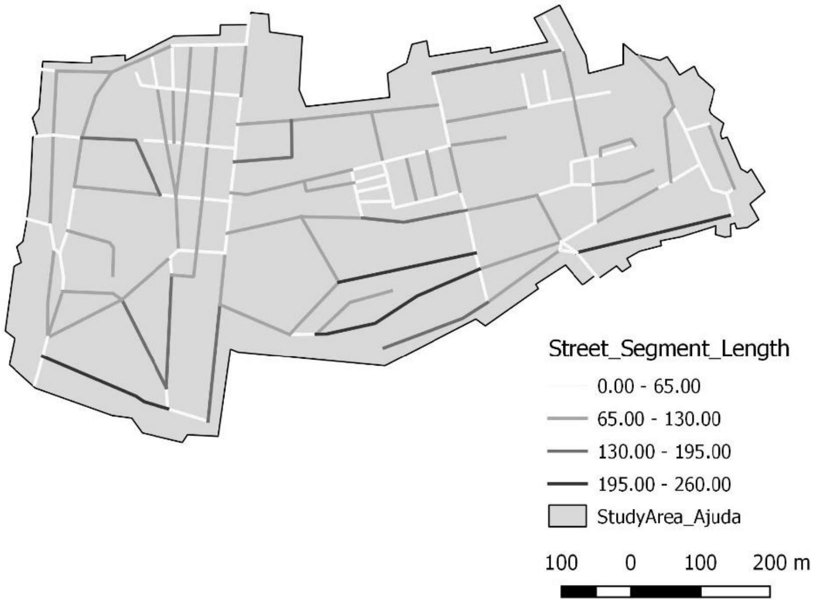
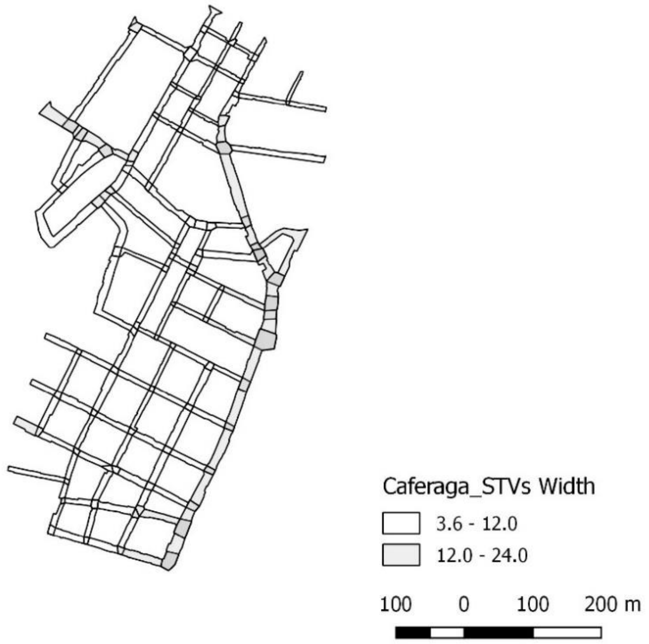


Figure B.14 : Lisbon street segment length.

APPENDIX C



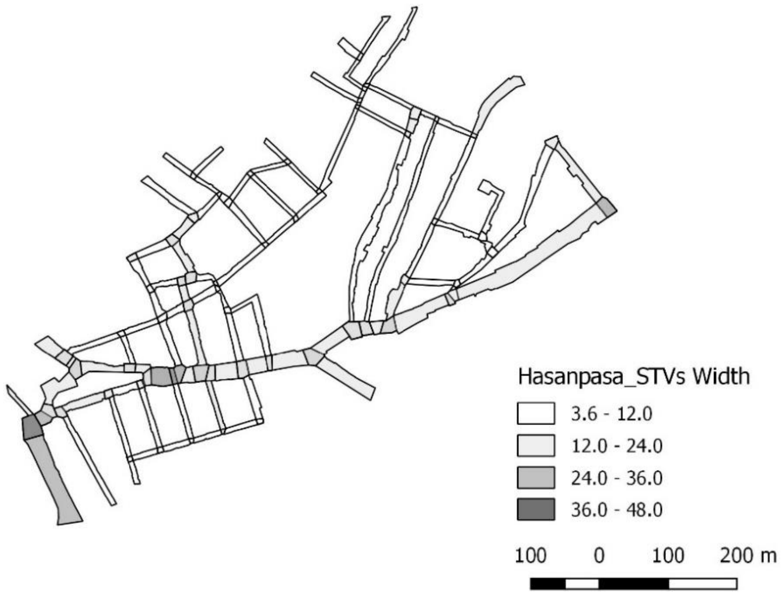
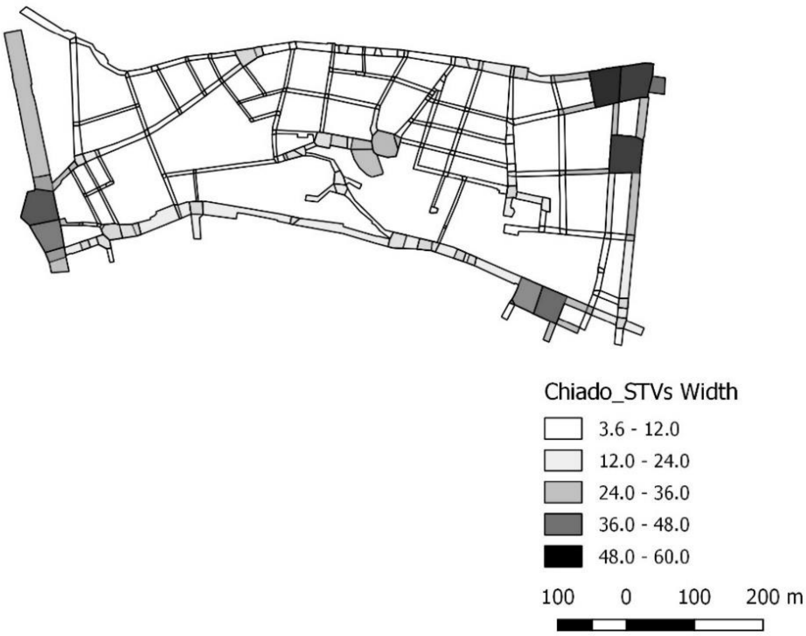


Figure C.1 : Istanbul STV widths.



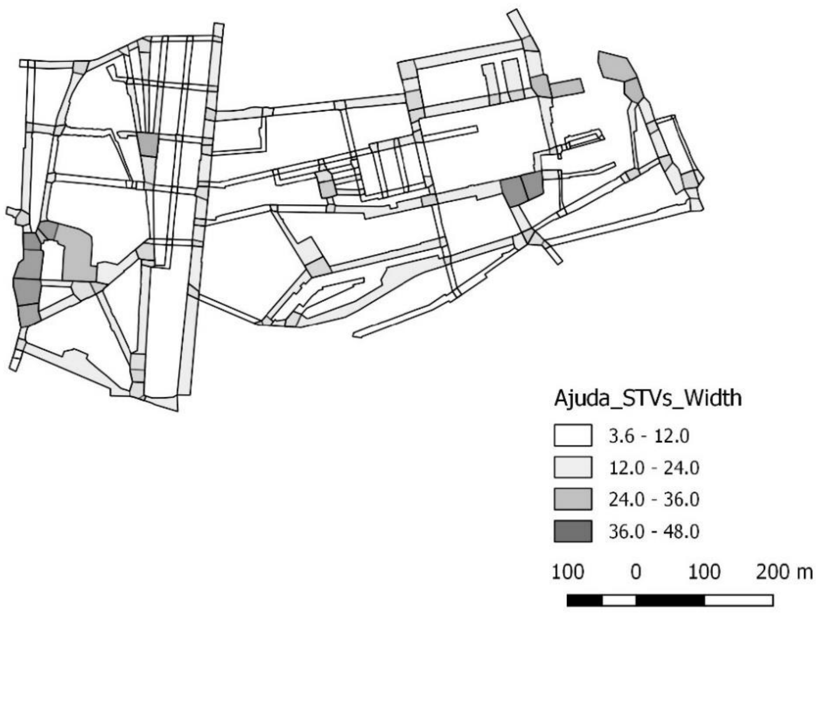


Figure C.2 : Lisbon STV widths.

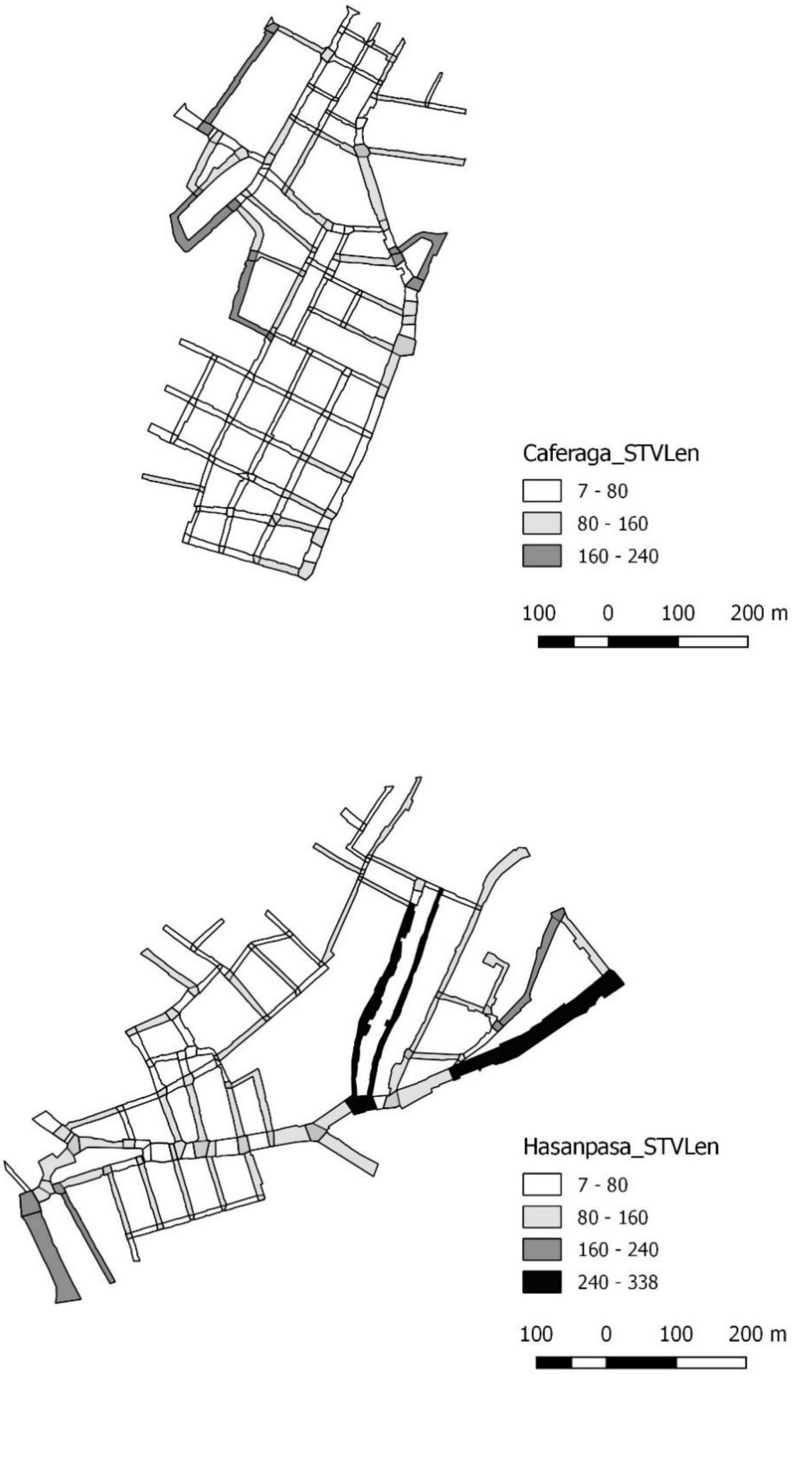


Figure C.3 : Istanbul STV lengths.

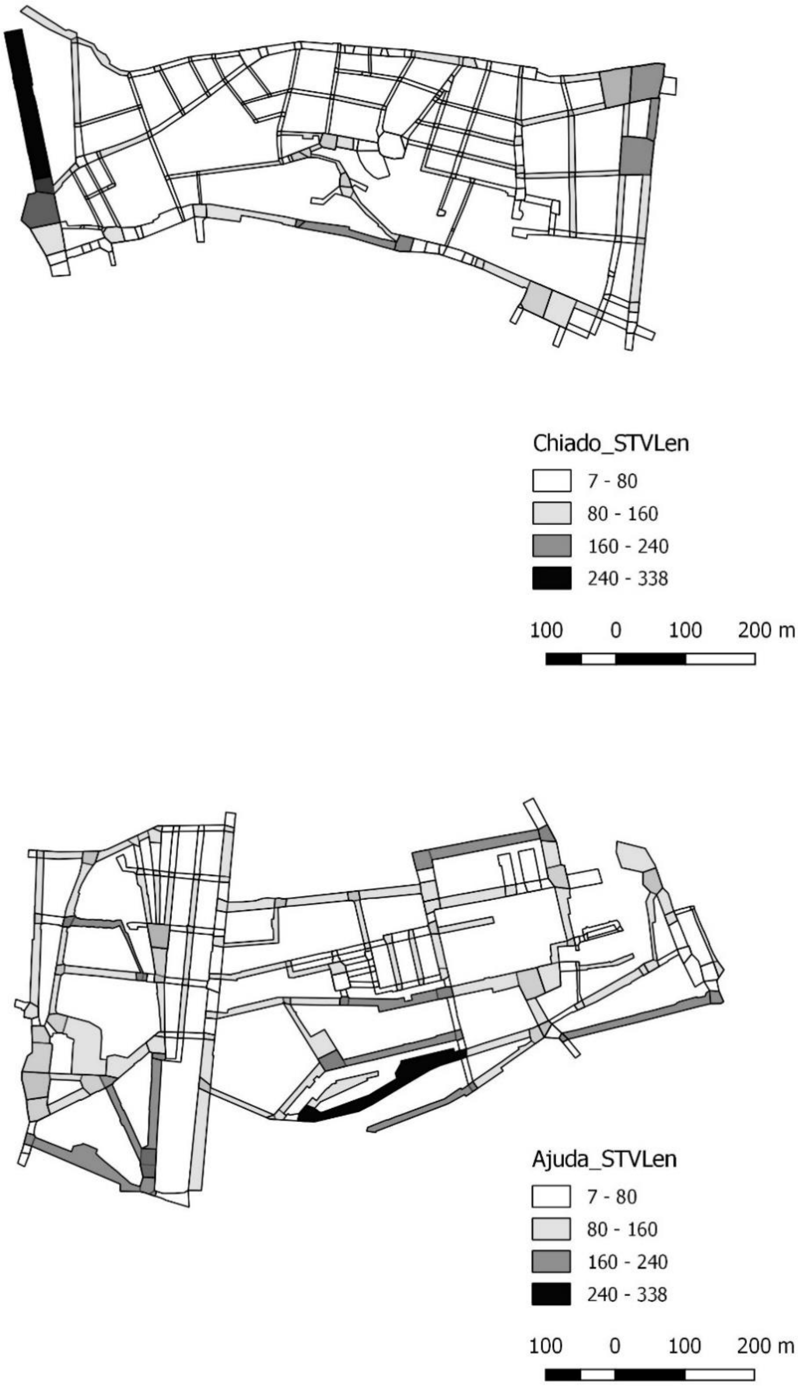
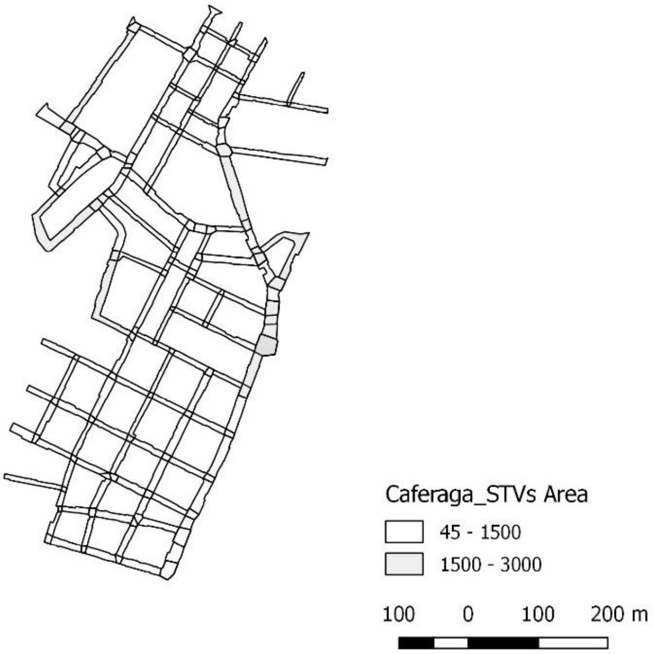


Figure C.4 : Lisbon STV lengths.



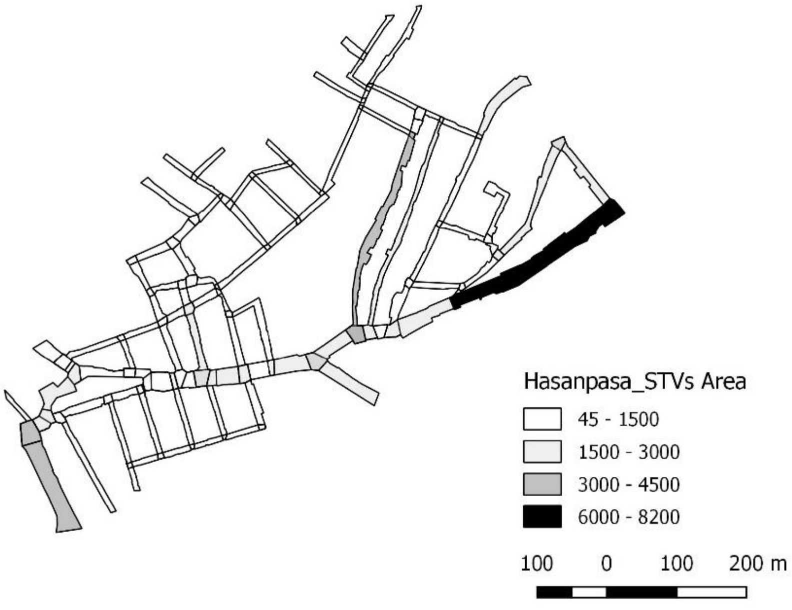


Figure C.5 : Istanbul STV areas.

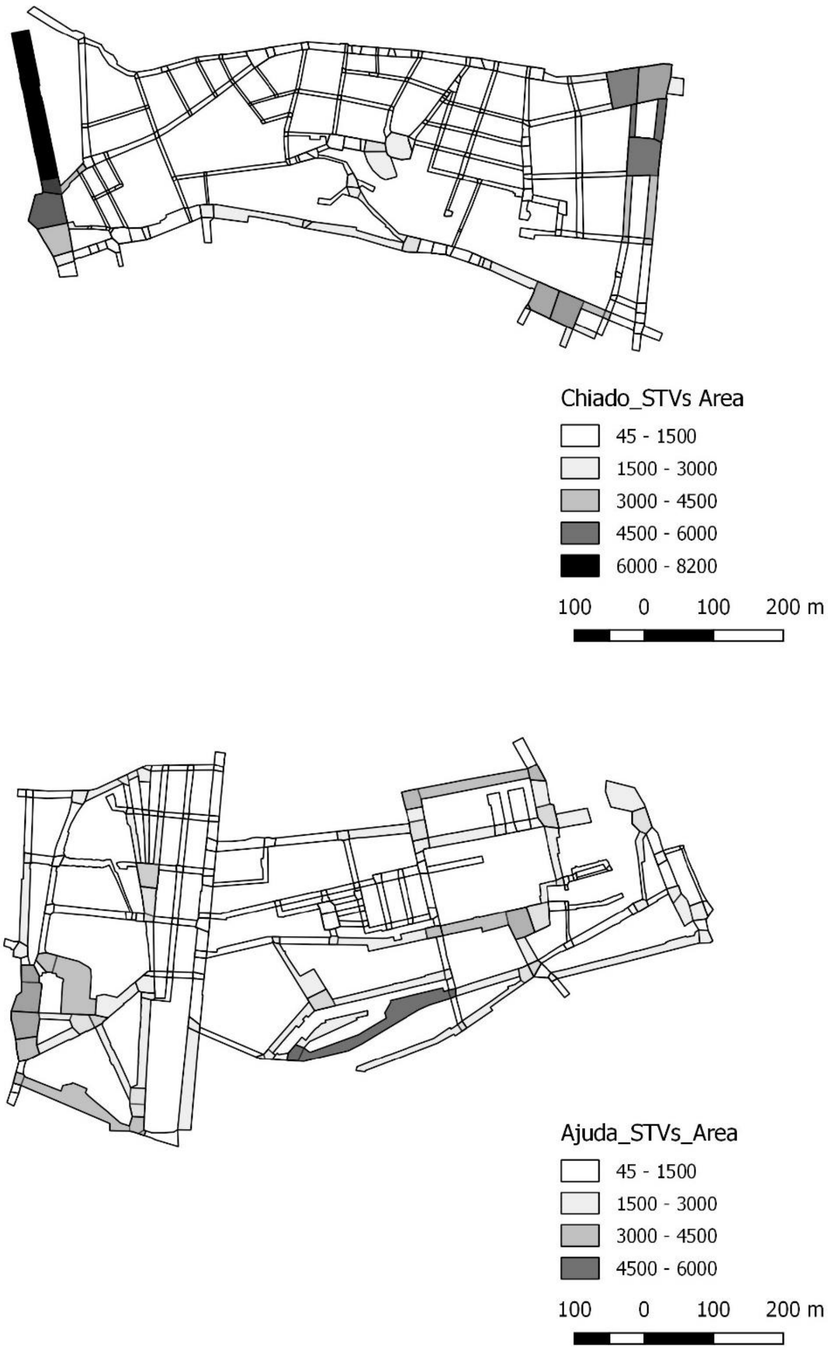


Figure C.6 : Lisbon STV areas.

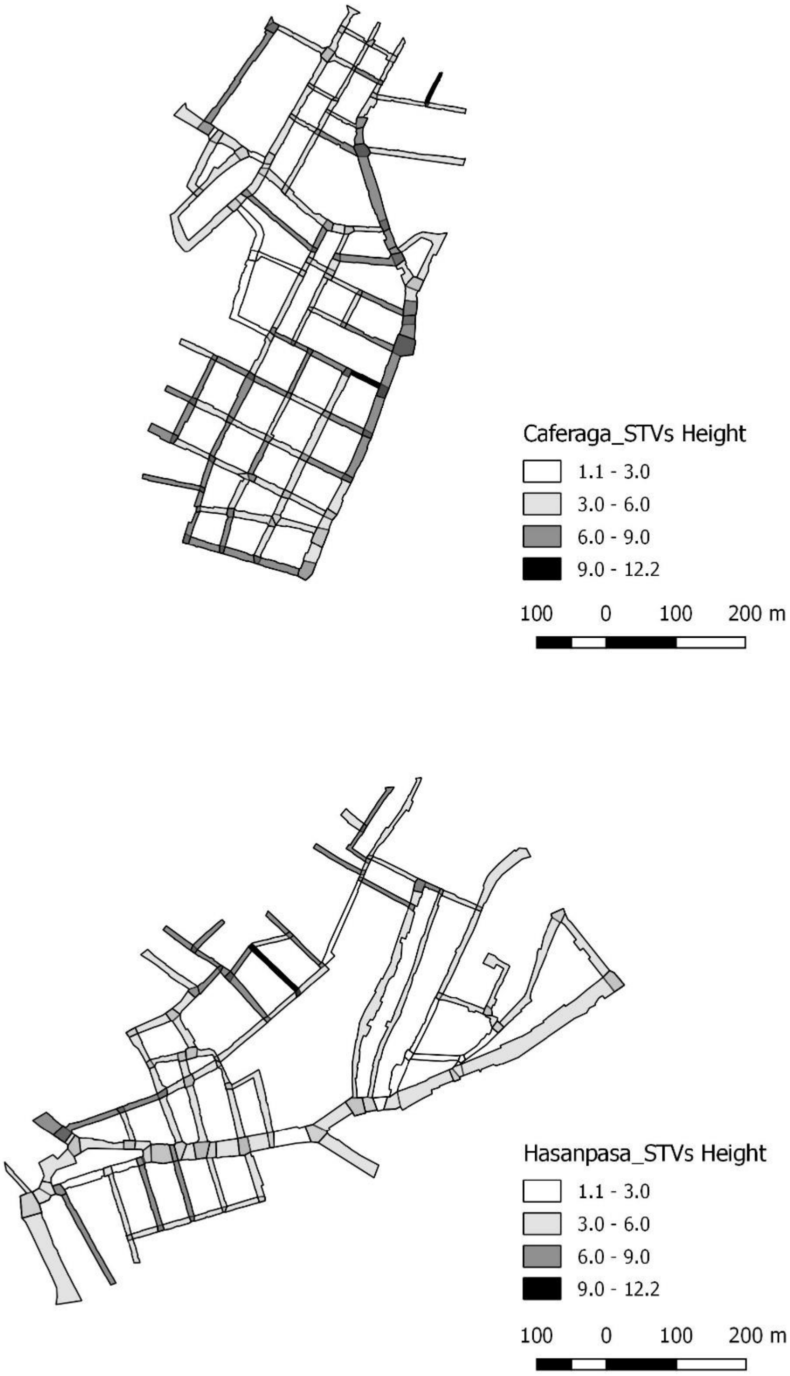
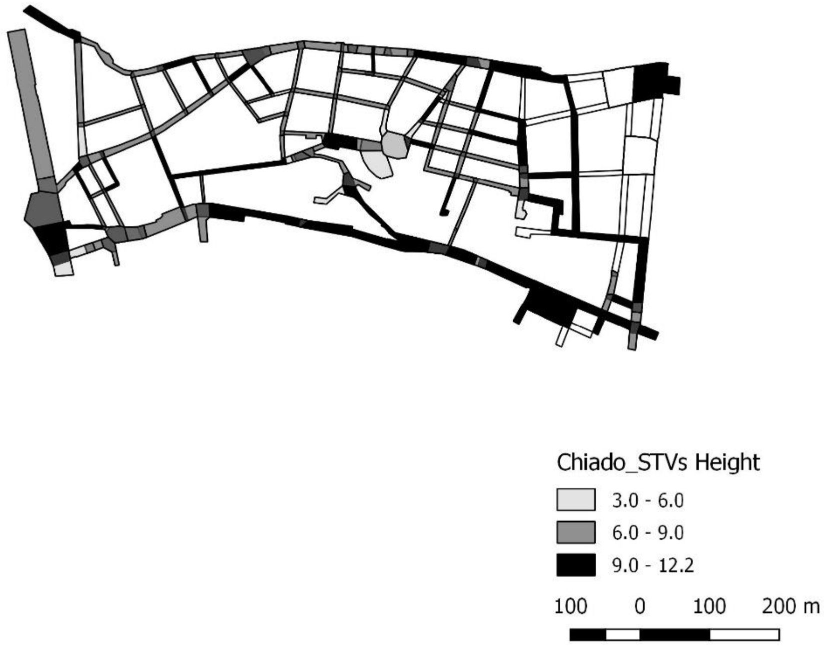


Figure C.7 : Istanbul STV heights.



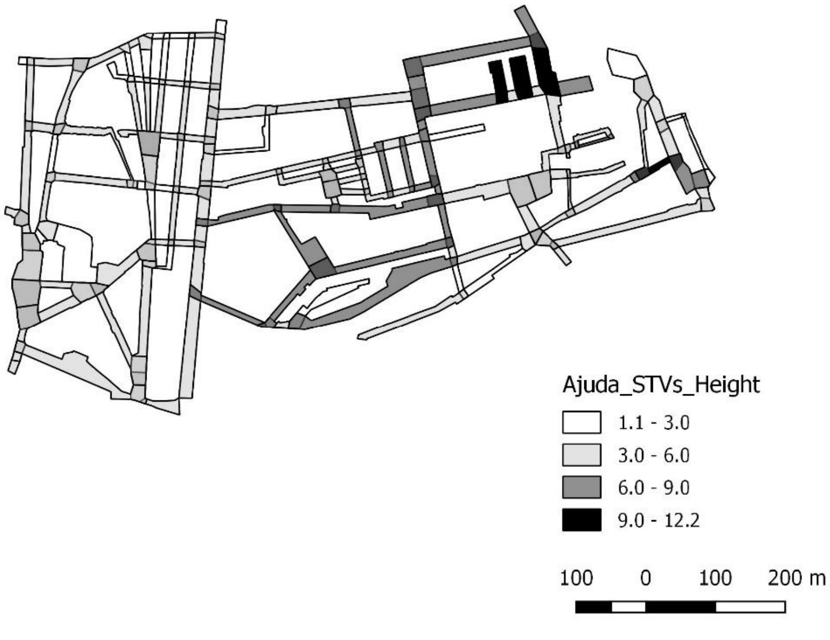
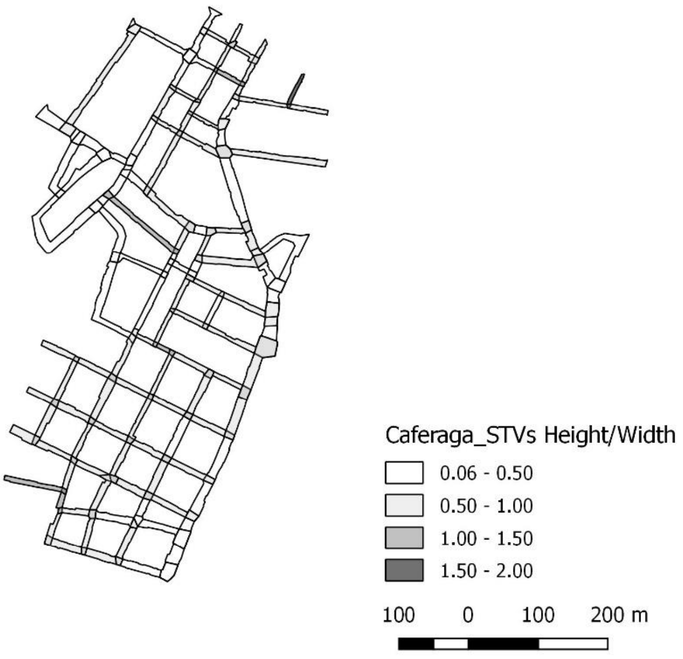


Figure C.8 : Lisbon STV heights.



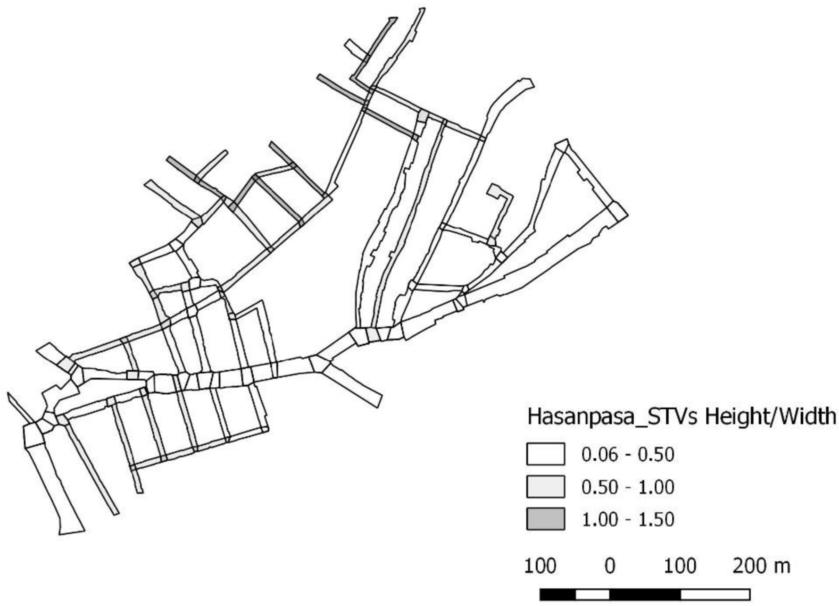


Figure C.9 : Istanbul STV height to width ratios.

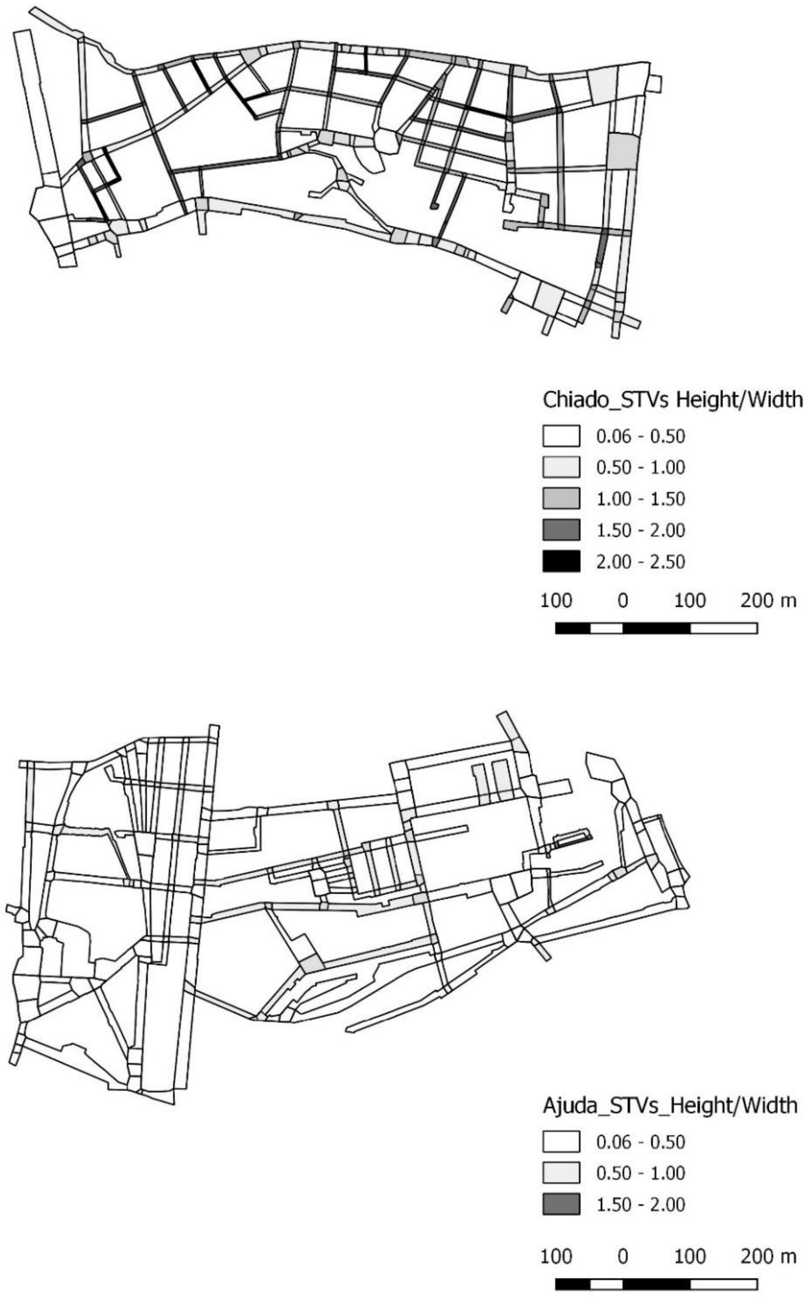


Figure C.10 : Lisbon STV height to width ratios.

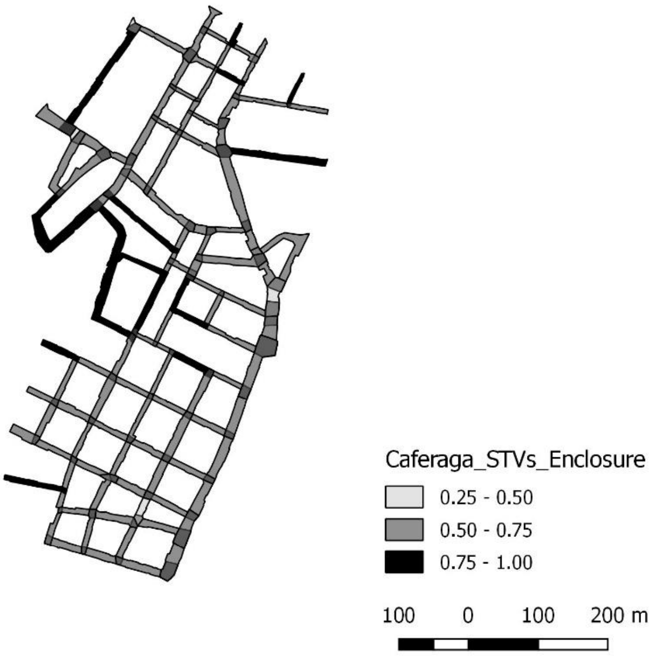


Figure C.11 : Istanbul STV enclosure values.

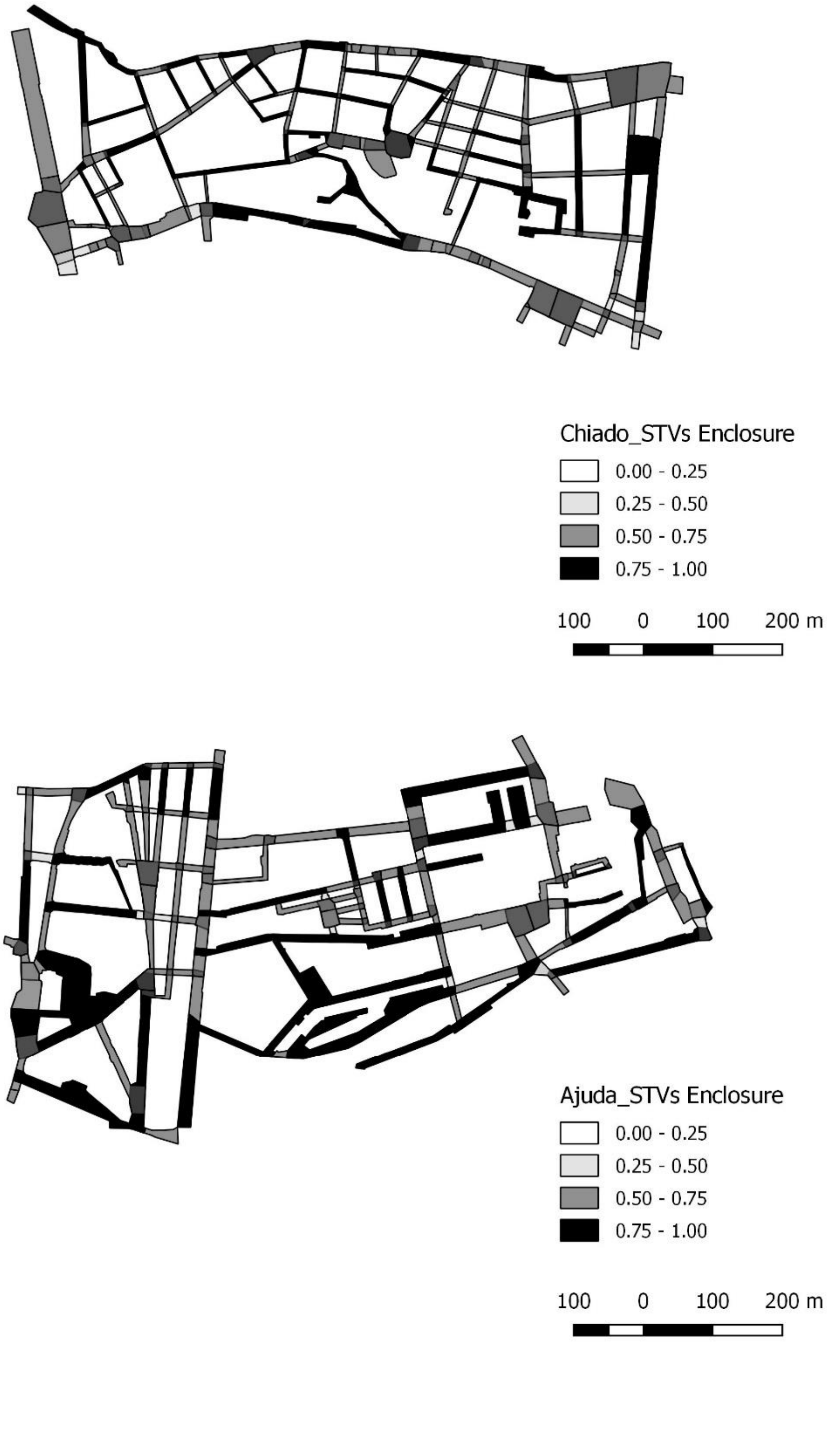
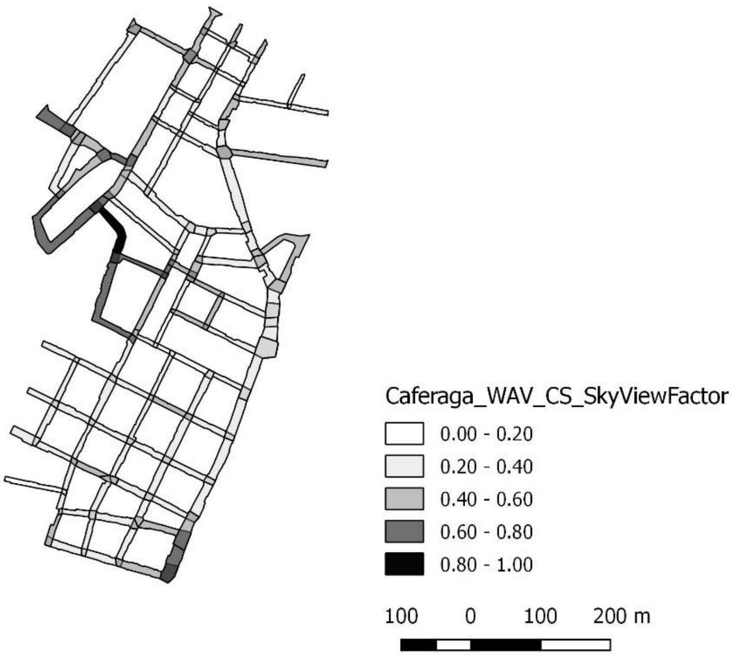


Figure C.12 : Lisbon STV enclosure values.



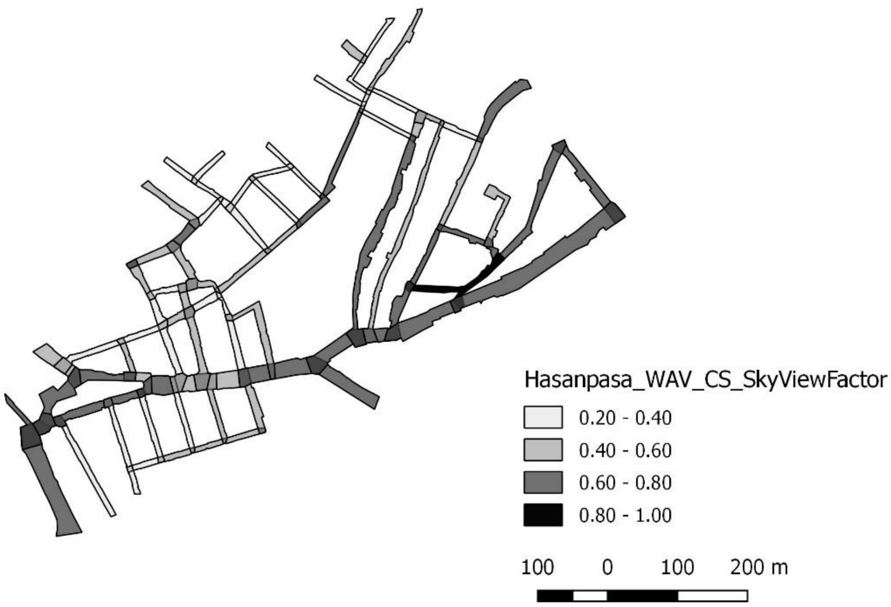


Figure C.13 : Istanbul average sky view factors of Convex-Voids.

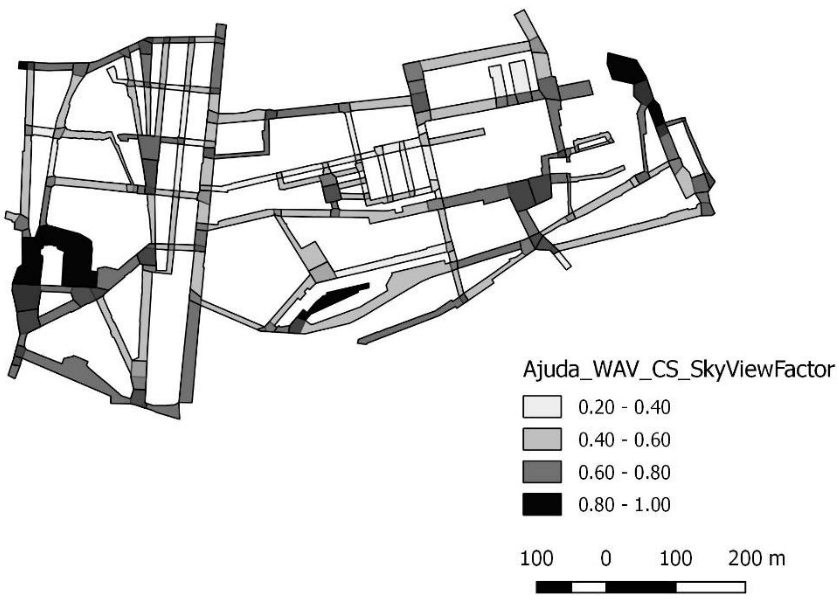


Figure C.14 : Lisbon average sky view factors of Convex-Voids.

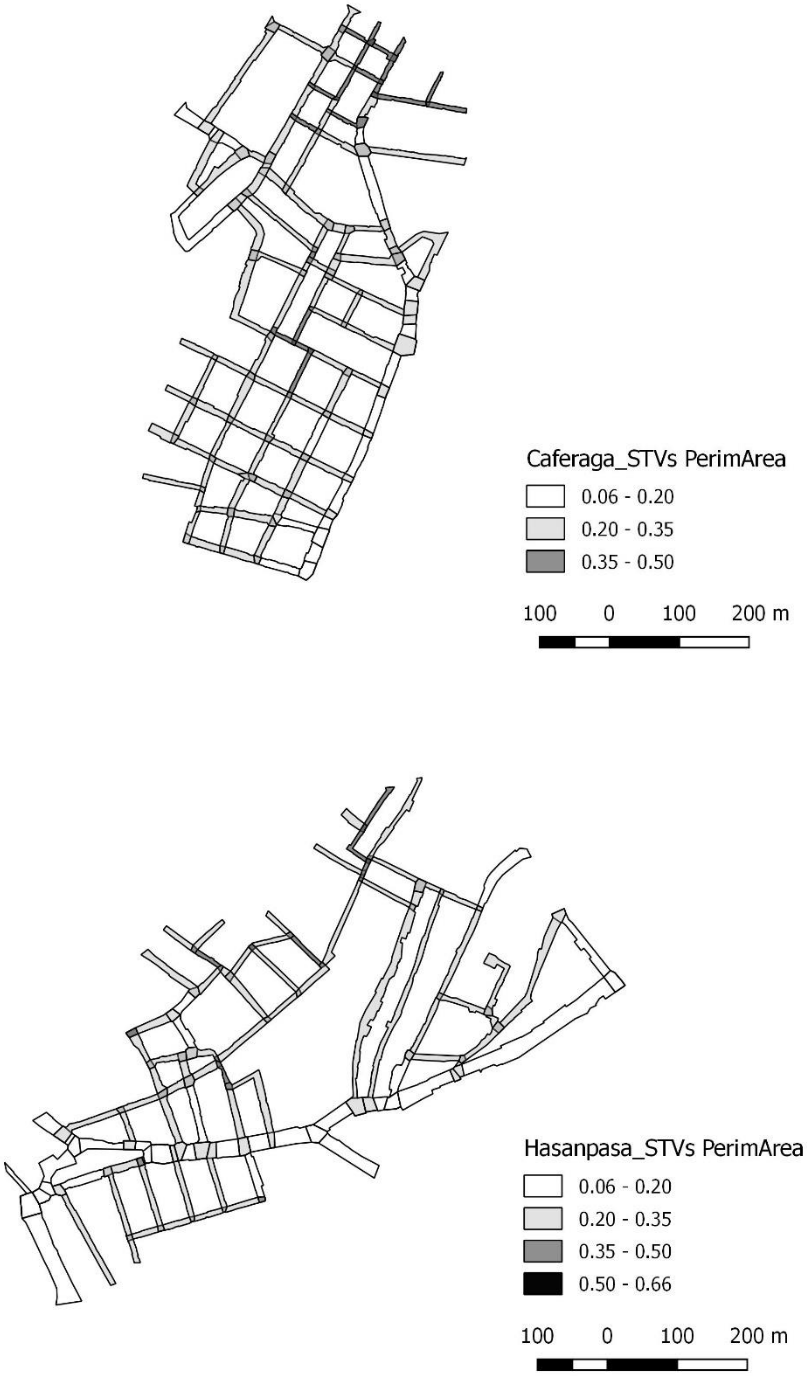
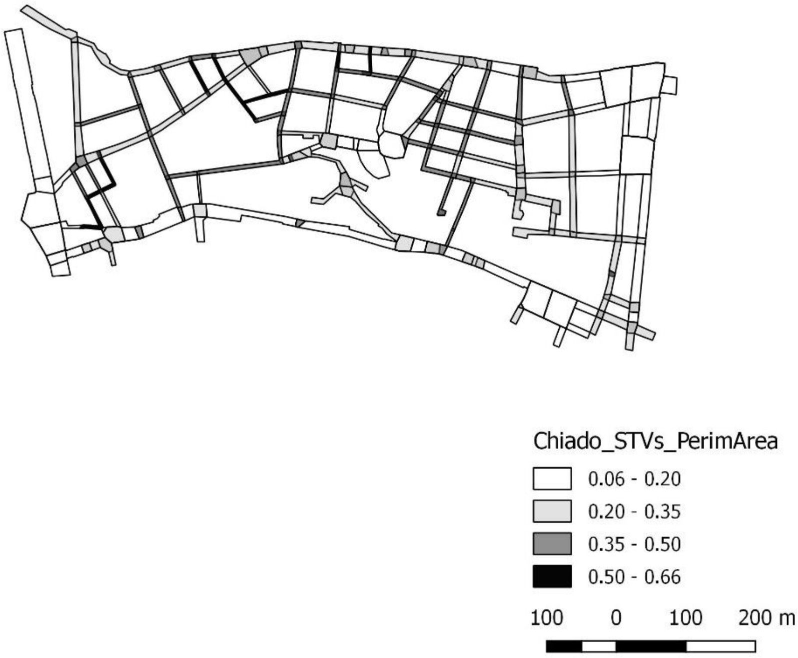


Figure C.15 : Istanbul STV perimeter/area ratios.



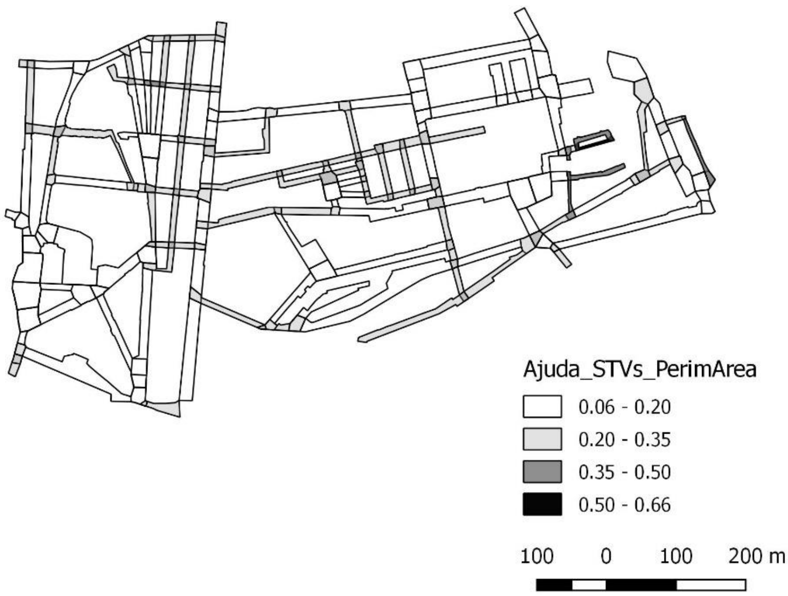
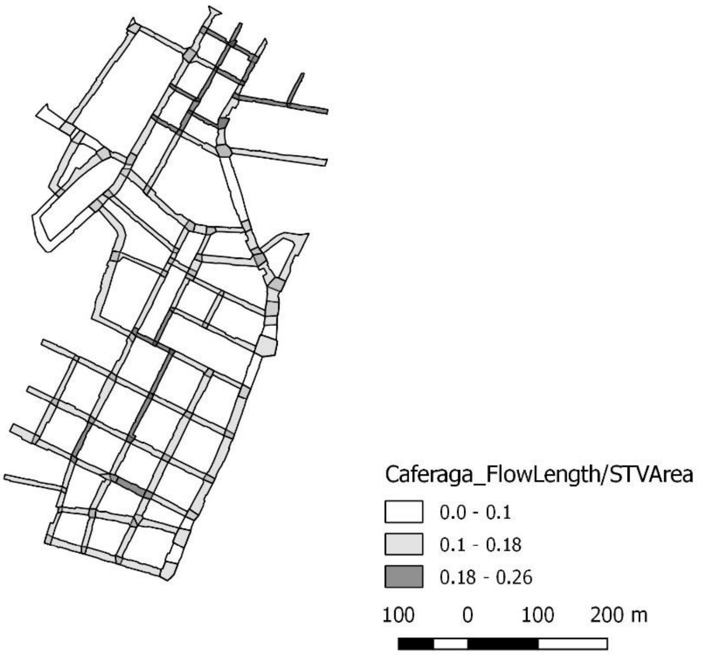


Figure C.16 : Lisbon STV perimeter/area ratios.



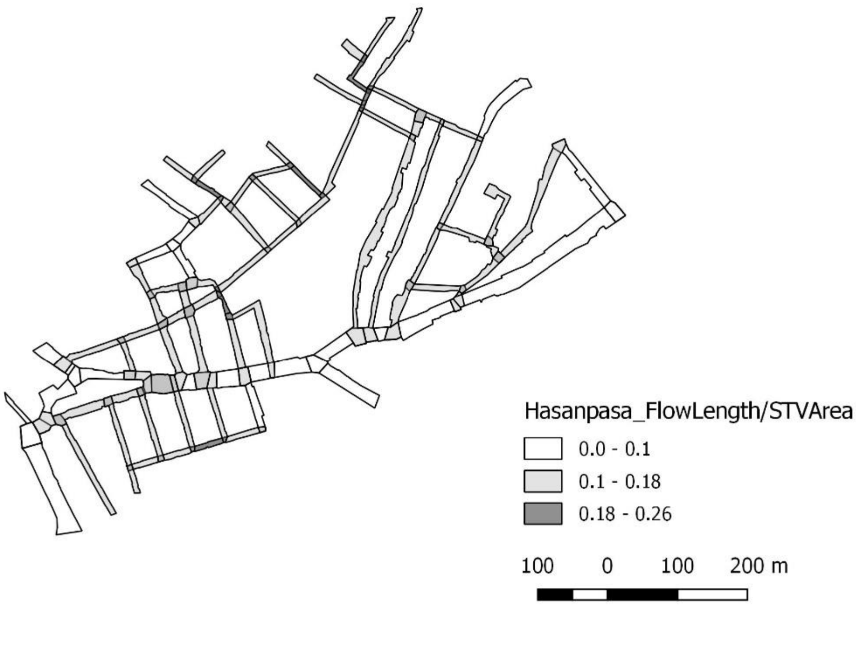


Figure C.17 : Istanbul total flow length per STV area.

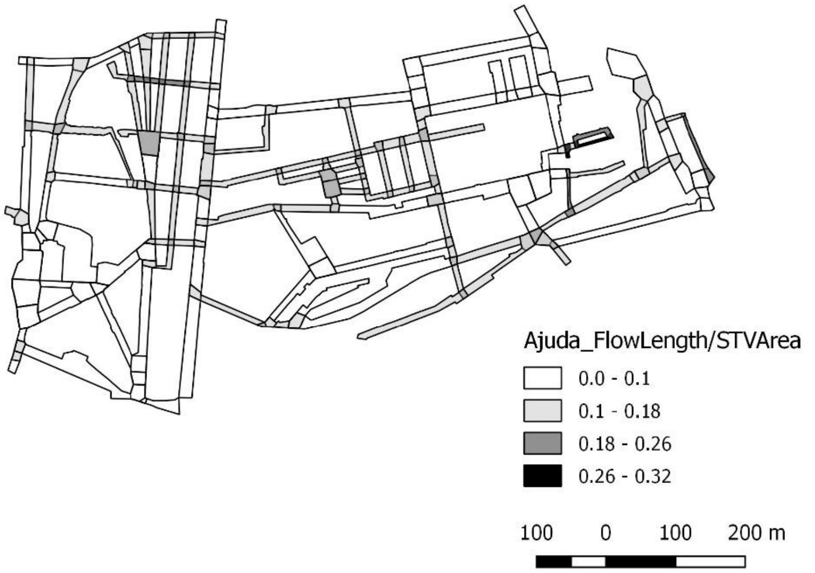
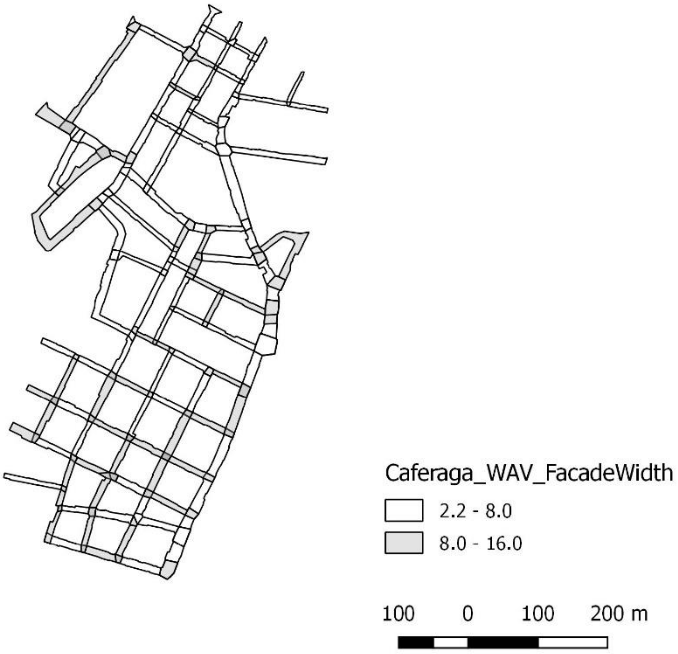


Figure C.18 : Lisbon total flow length per STV area.



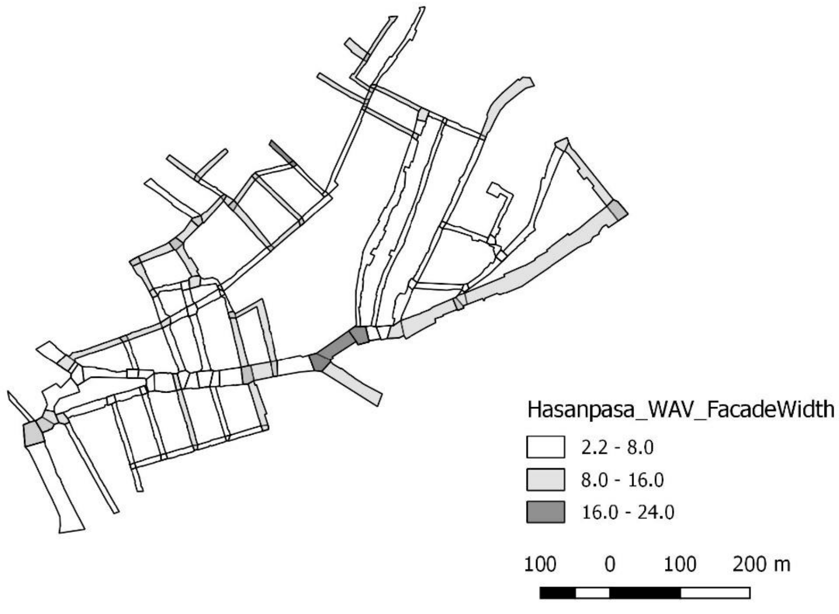
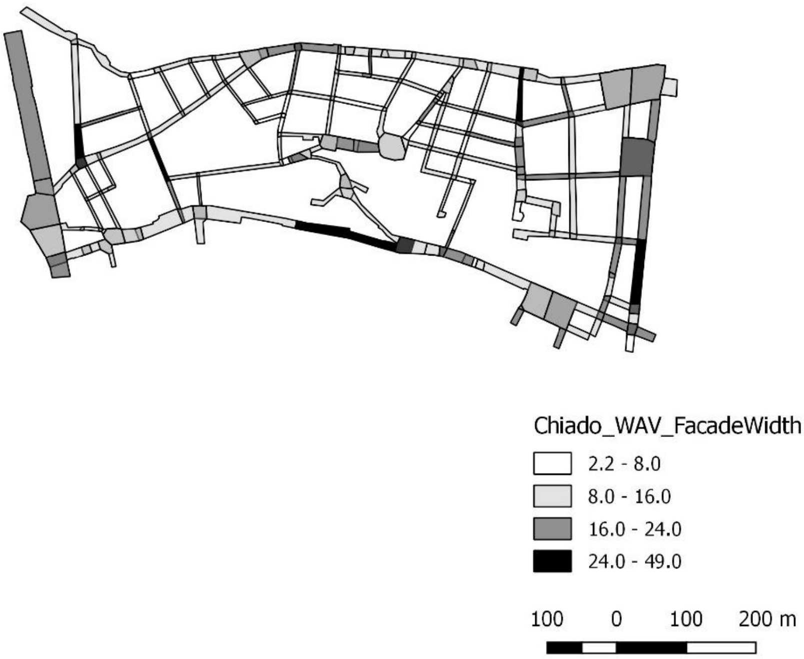


Figure C.19 : Istanbul WAv of façade widths.



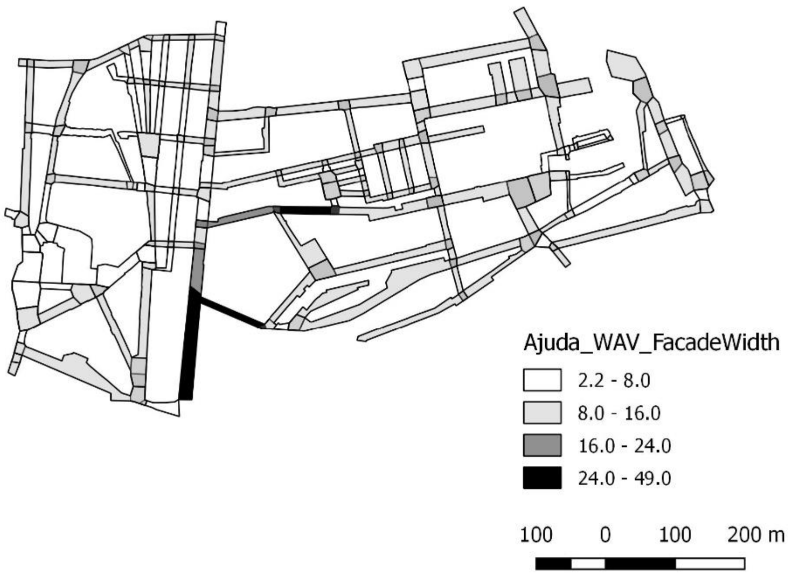


Figure C.20 : Lisbon WAv of façade widths**.**

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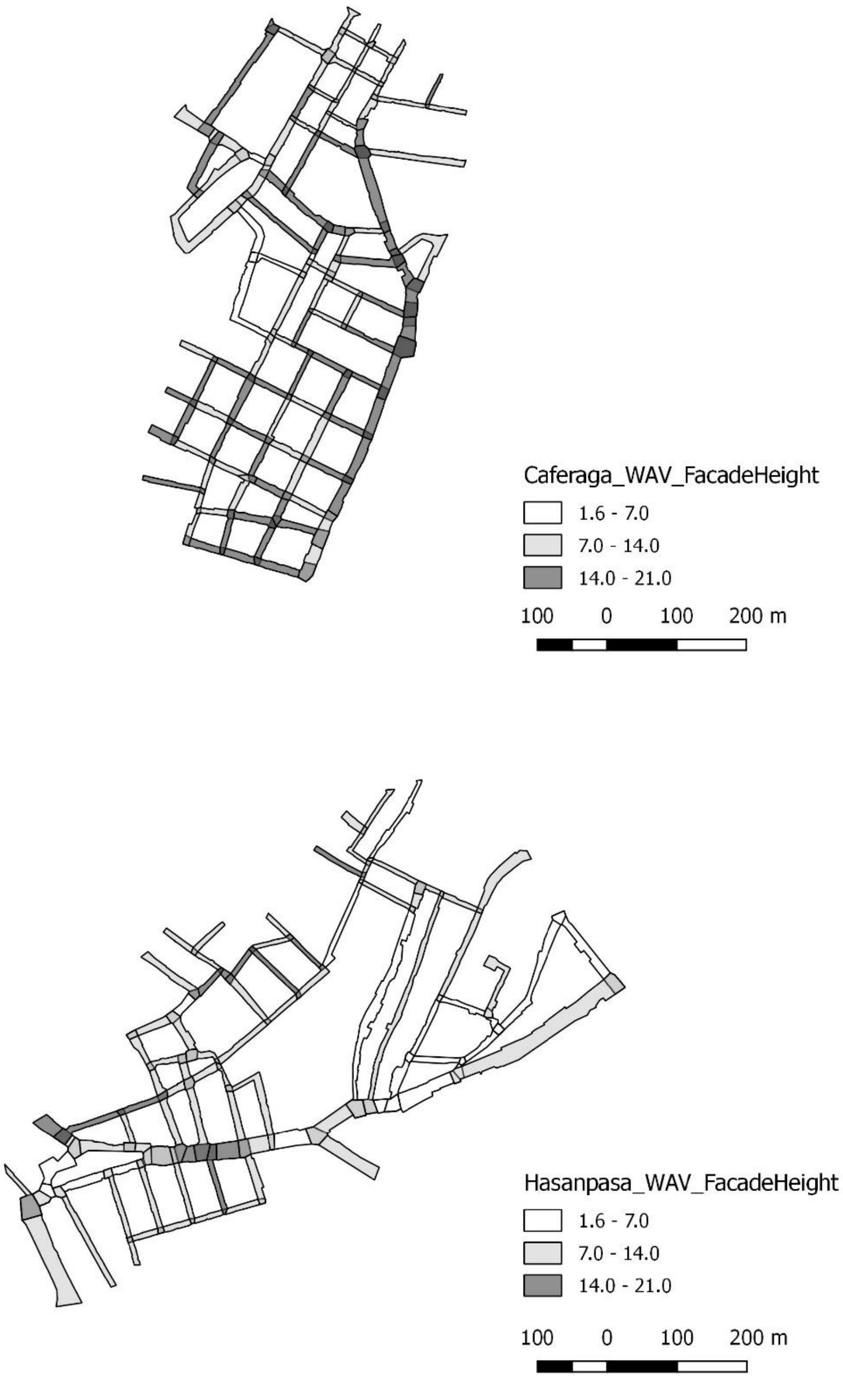
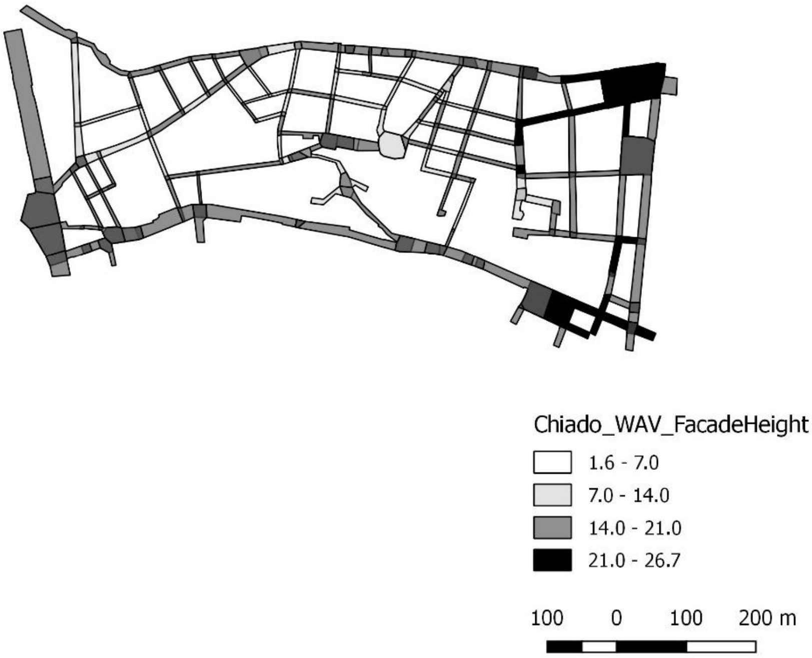


Figure C.21 : Istanbul WAv of façade heights.



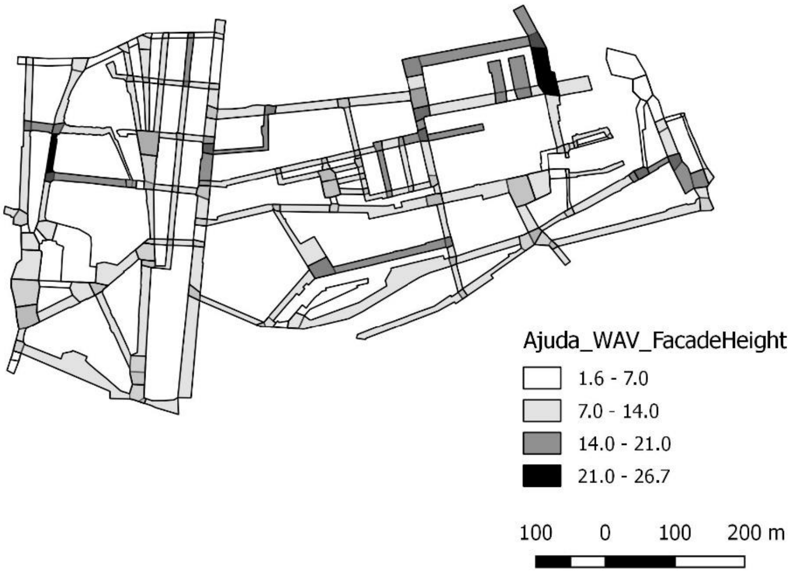
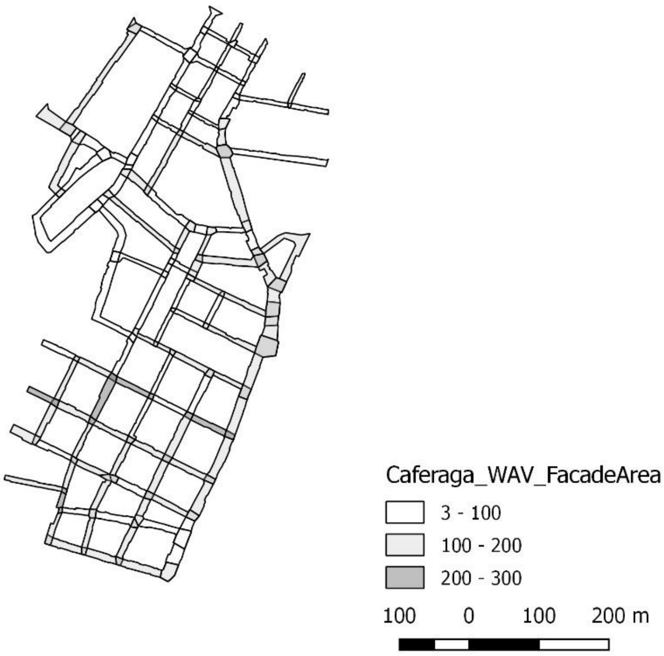


Figure C.22 : Lisbon WAv of façade heights.



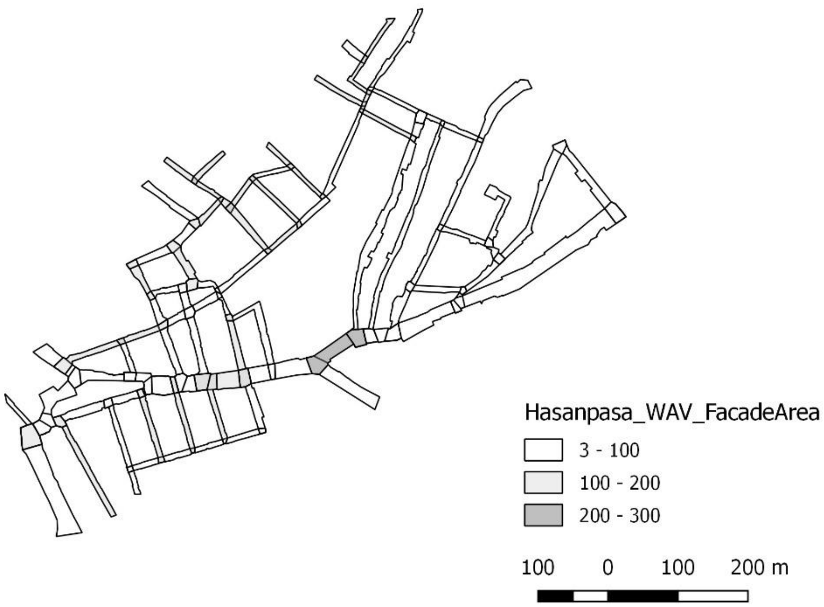
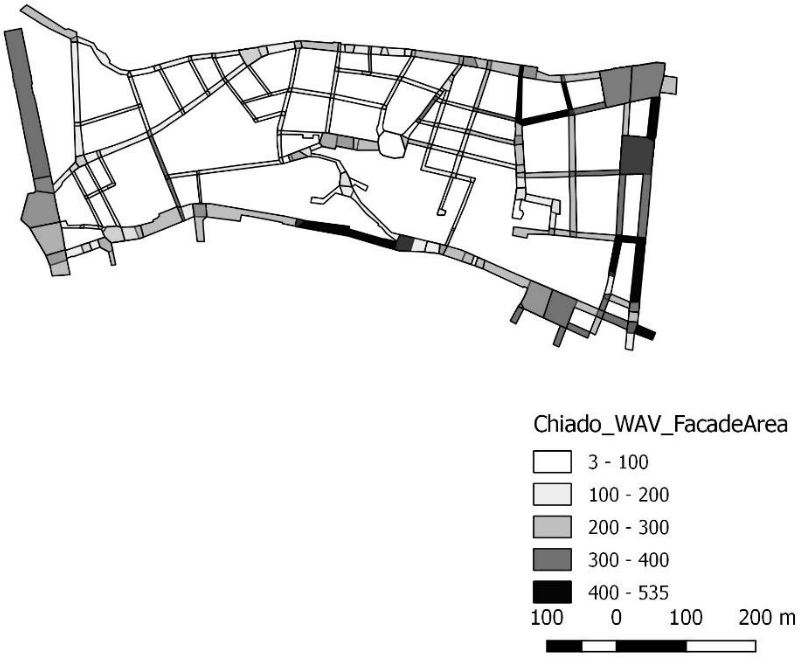


Figure C.23 : Istanbul WAv of façade areas.



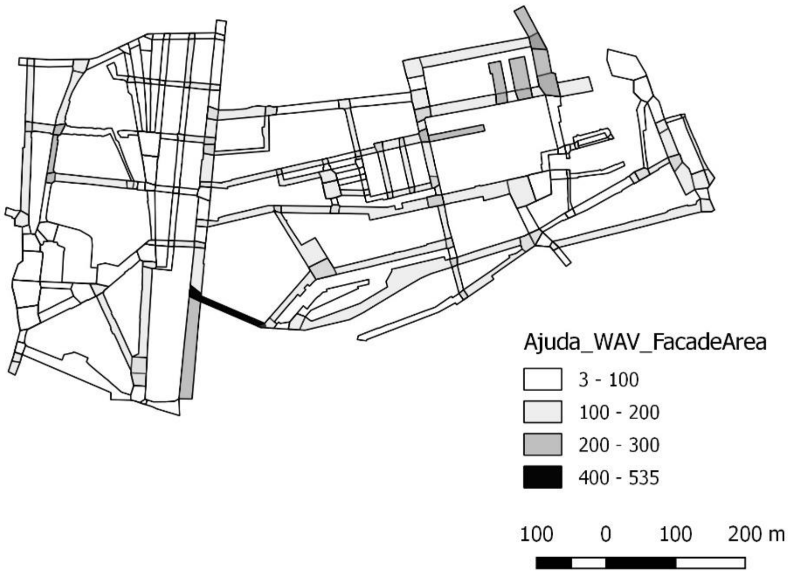


Figure C.24 : Lisbon WAv of façade areas.

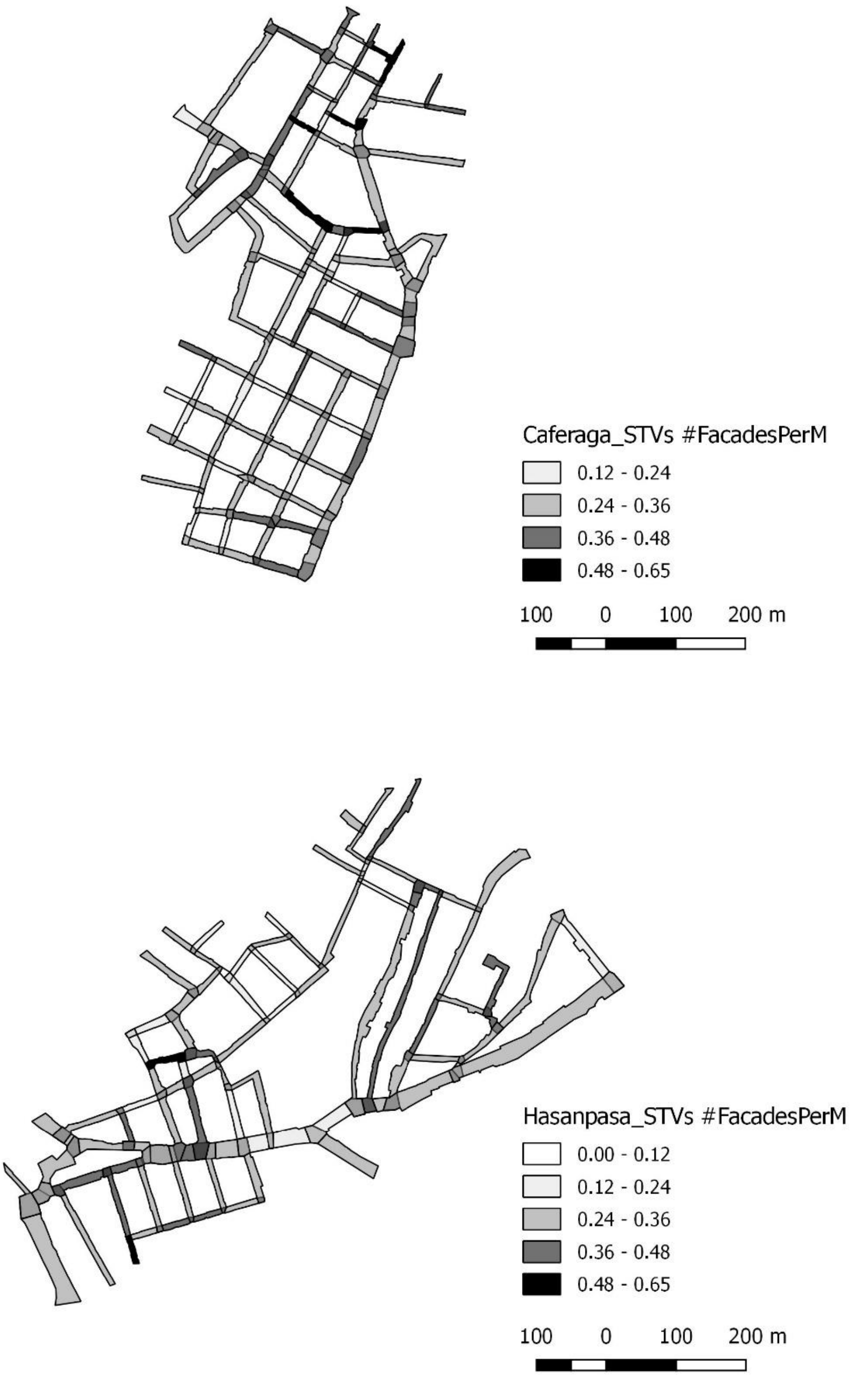


Figure C.25 : Istanbul number of facades per STV length.

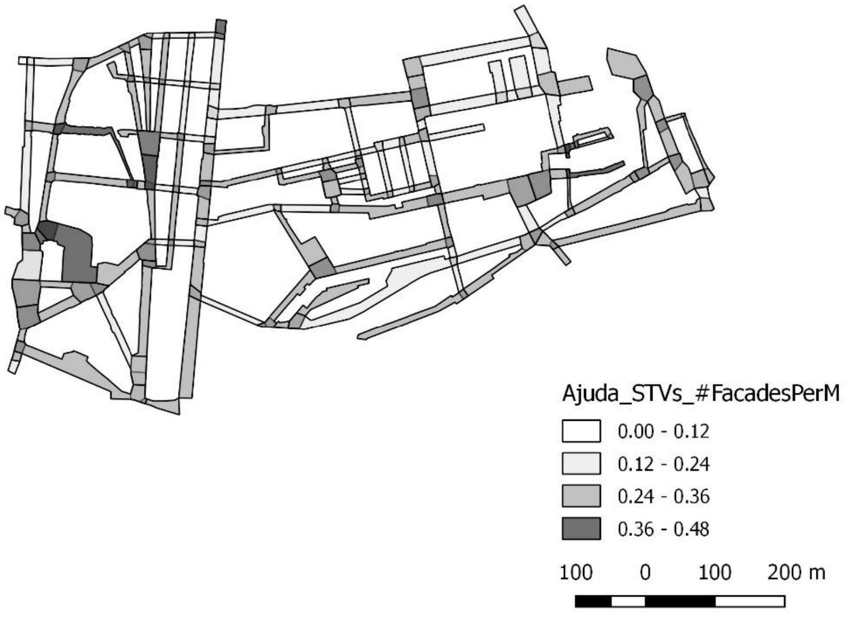


Figure C.26 : Lisbon number of facades per STV length.

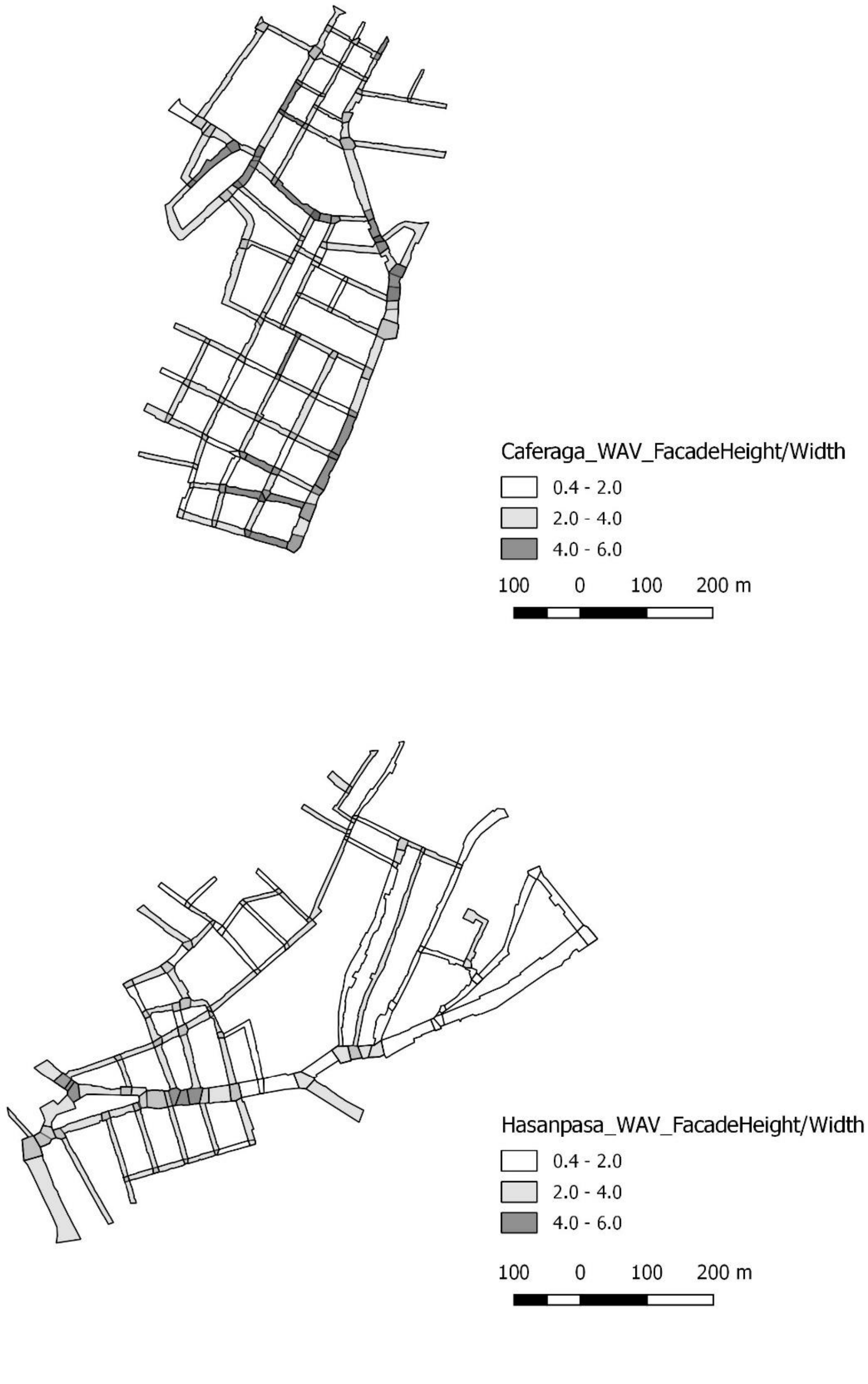


Figure C.27 : Istanbul WAv of facades height to width ratio.

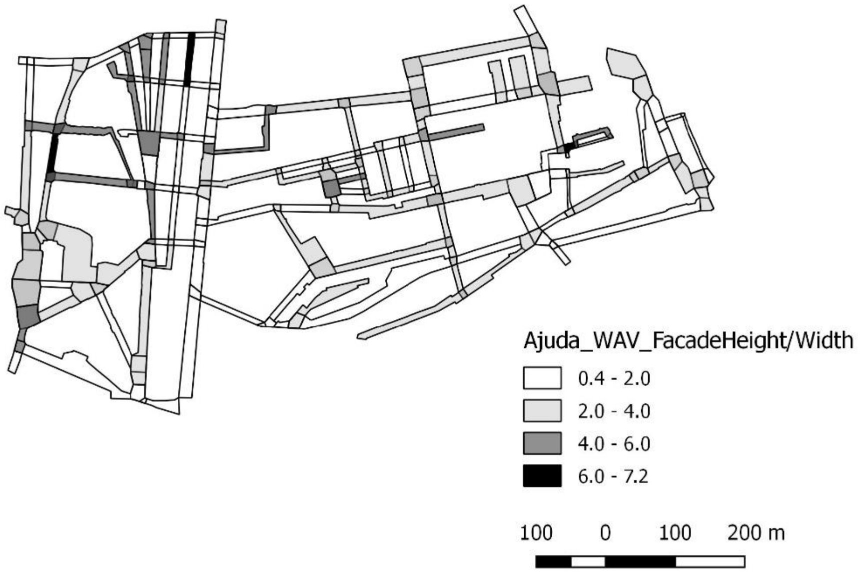
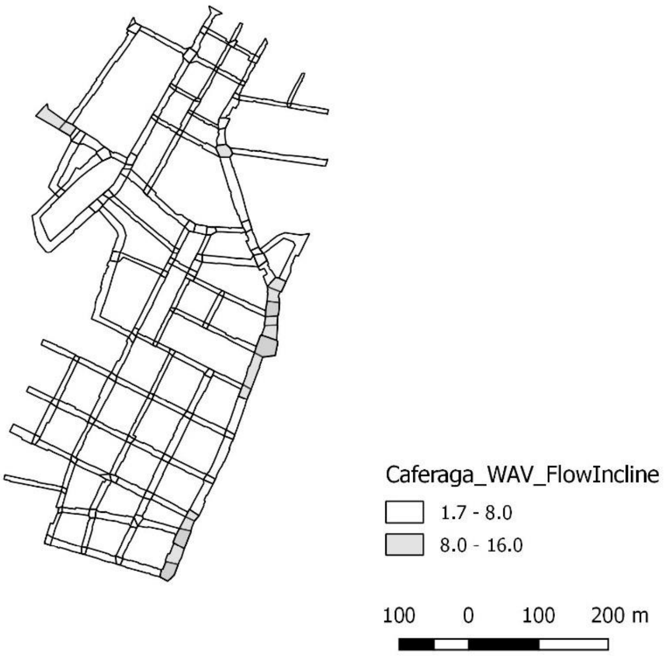


Figure C.28 : Lisbon WAv of facades height to width ratio.



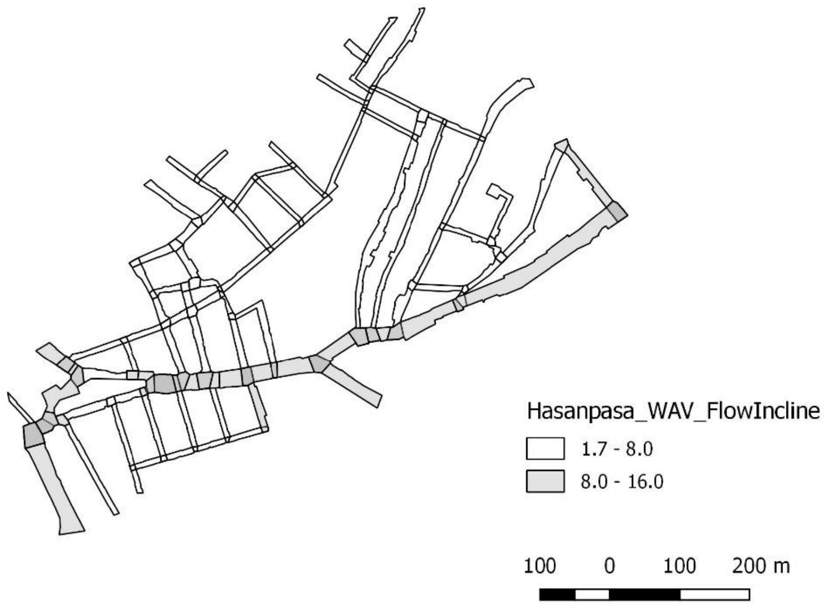
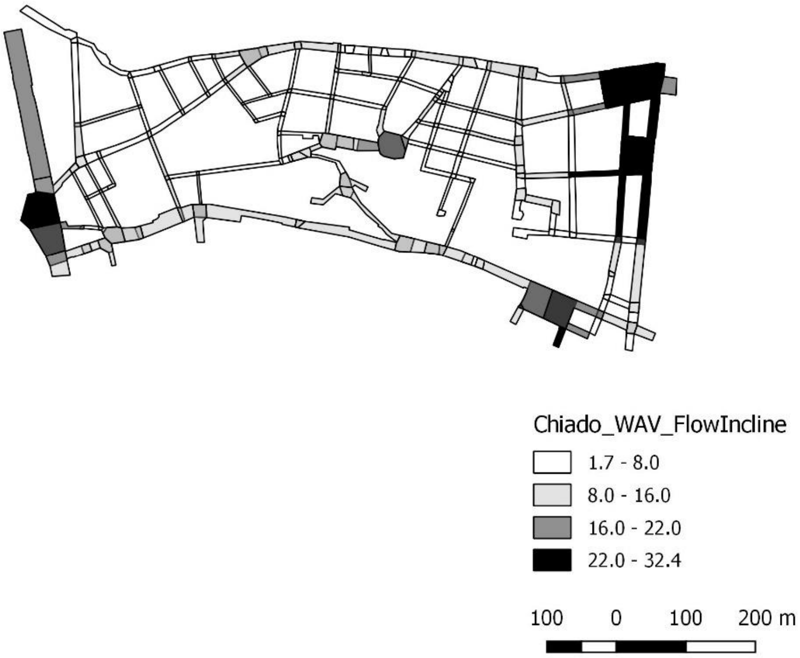


Figure C.29 : Istanbul WAv of flow inclines.



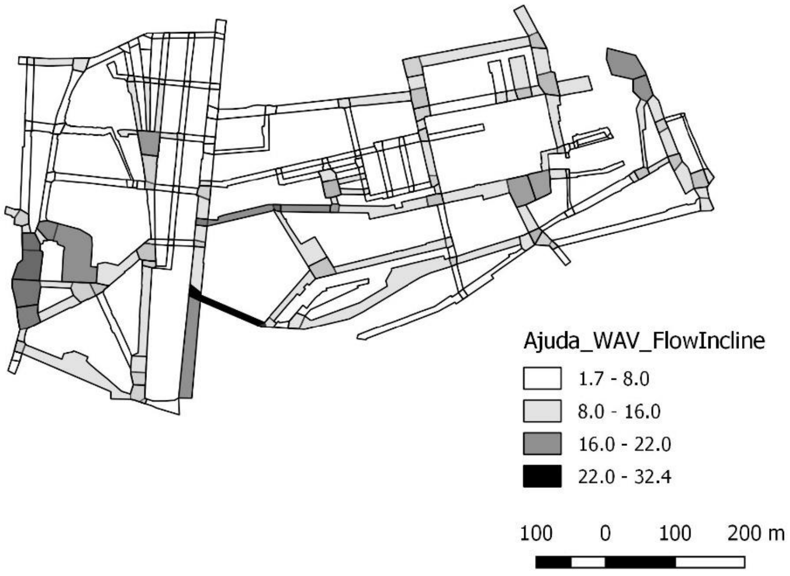


Figure C.30 : Lisbon WAv of flow inclines.

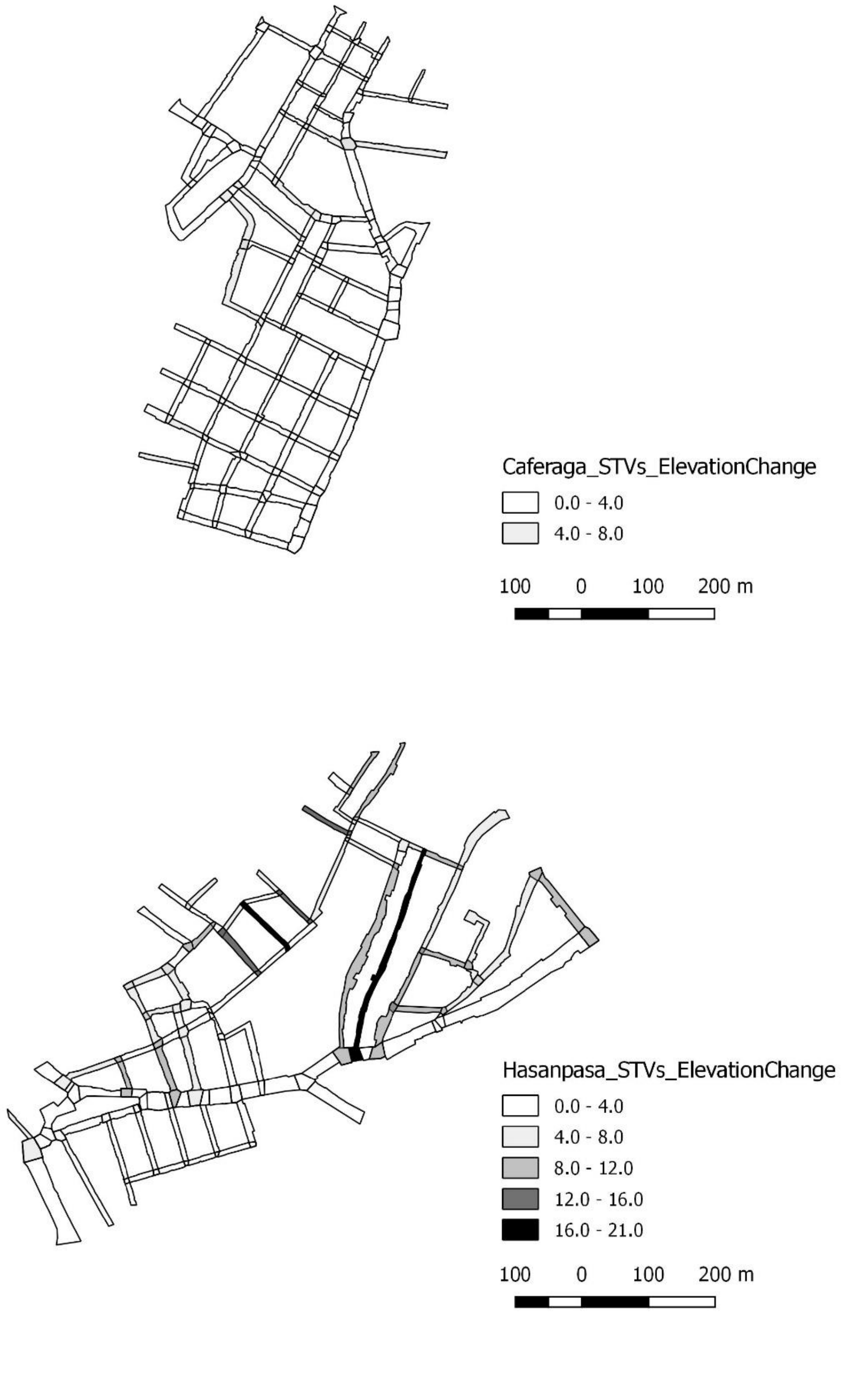
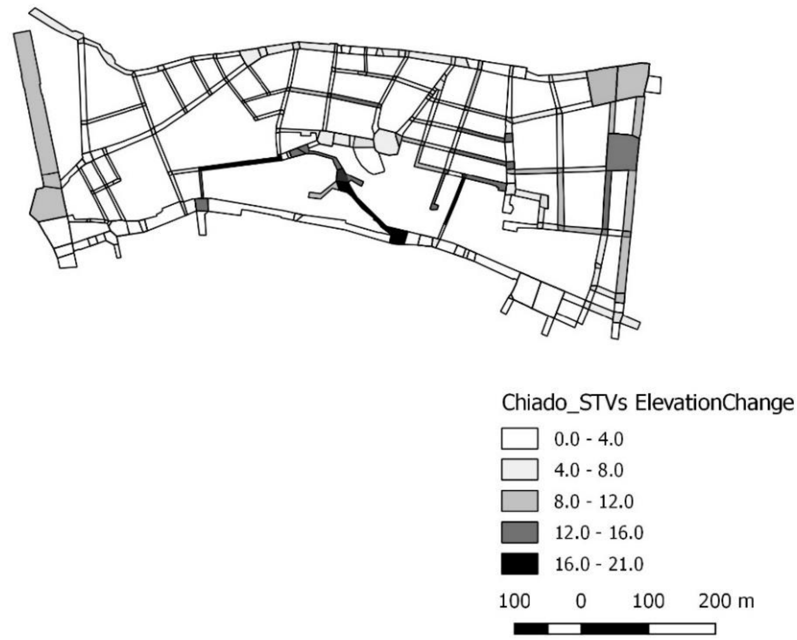


Figure C.31 : Istanbul max elevation change per STV.



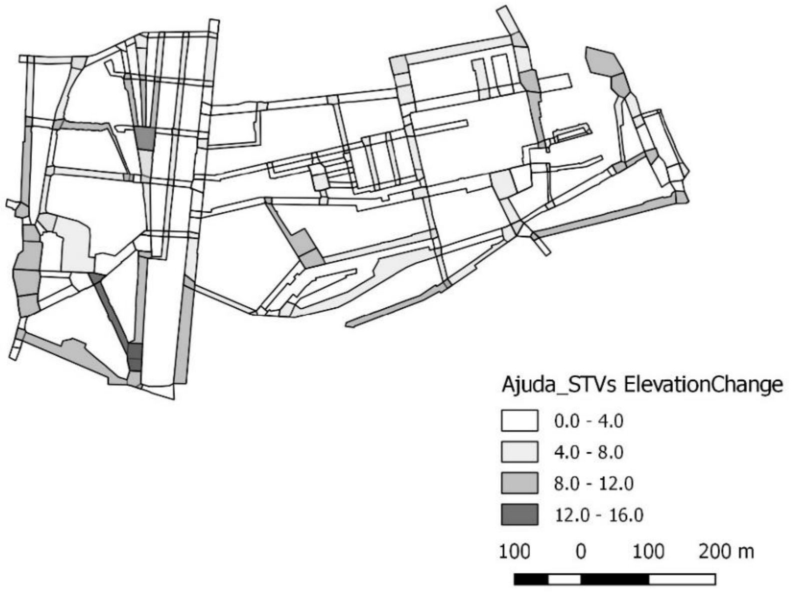


Figure C.32 : Lisbon max elevation change per STV.

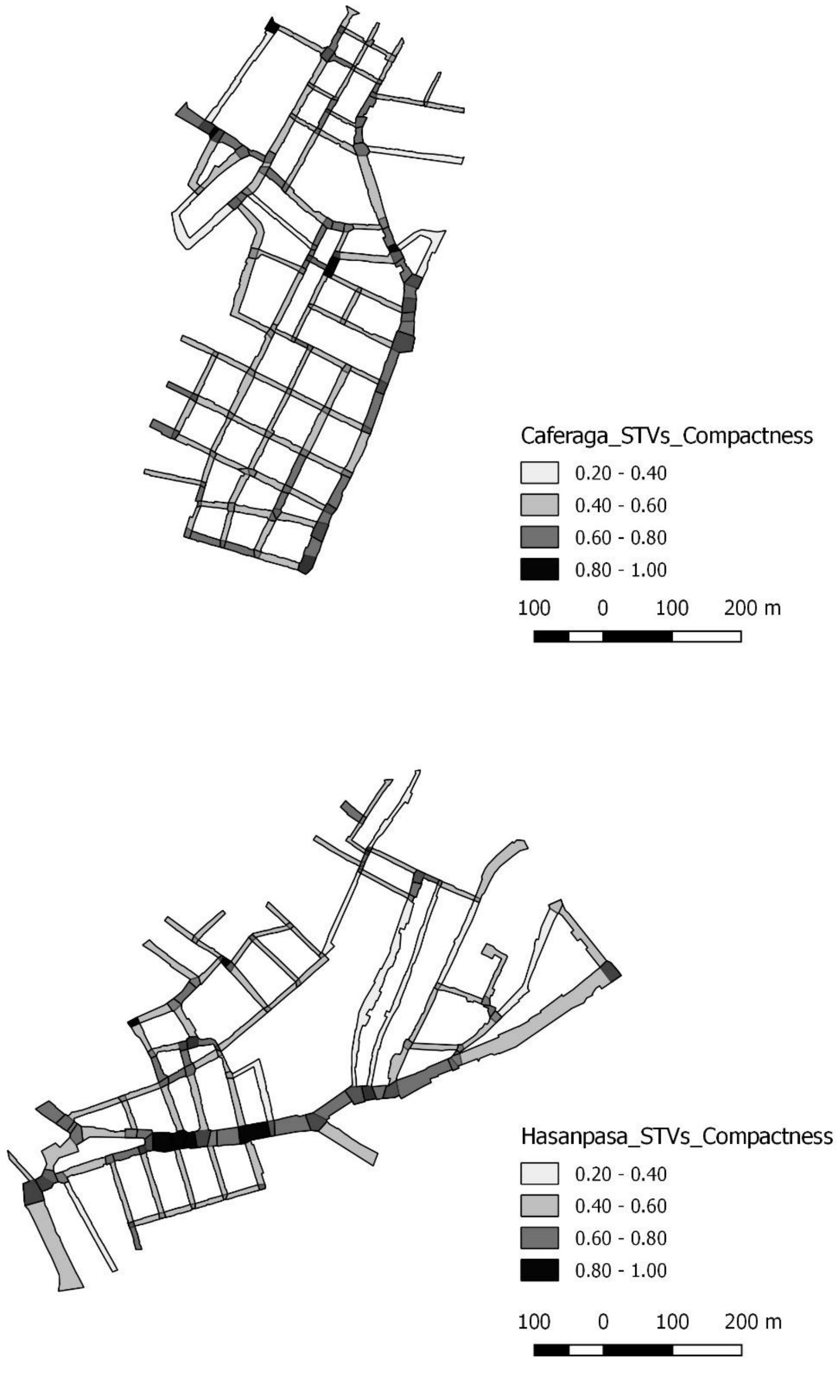


Figure C.33 : Istanbul STV Compactness.

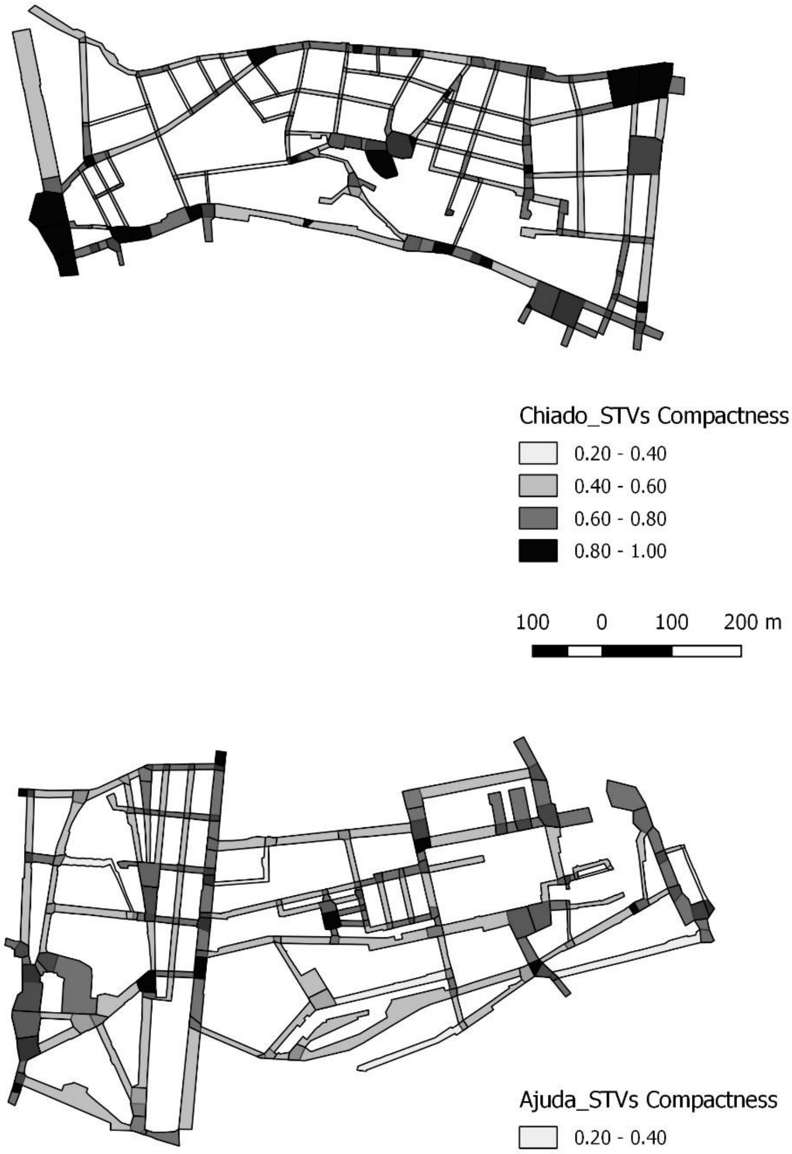
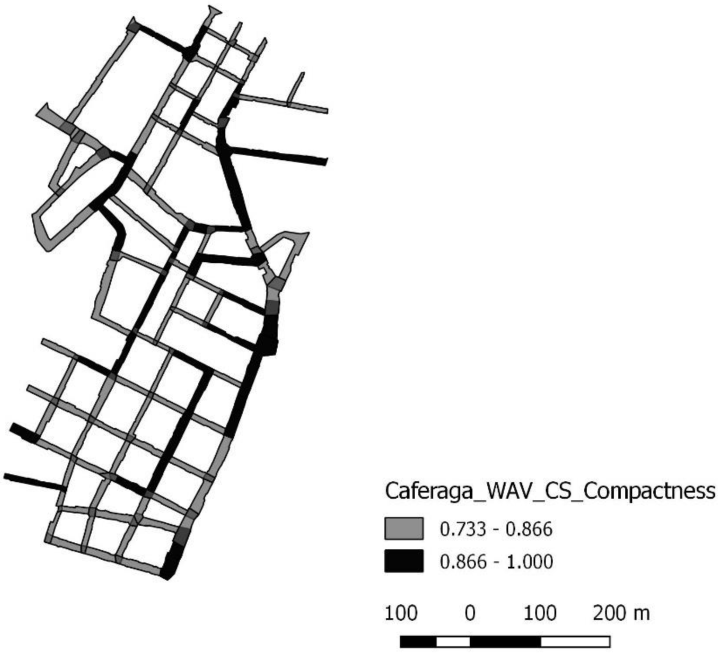


Figure C.34 : Lisbon STV Compactness.



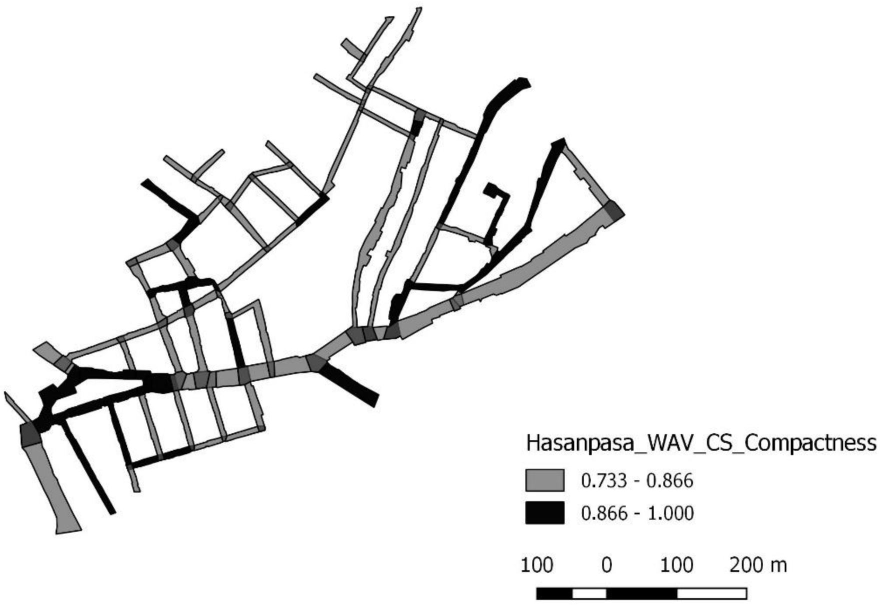


Figure C.35 : Istanbul WAv of Convex-Void Compactness values.

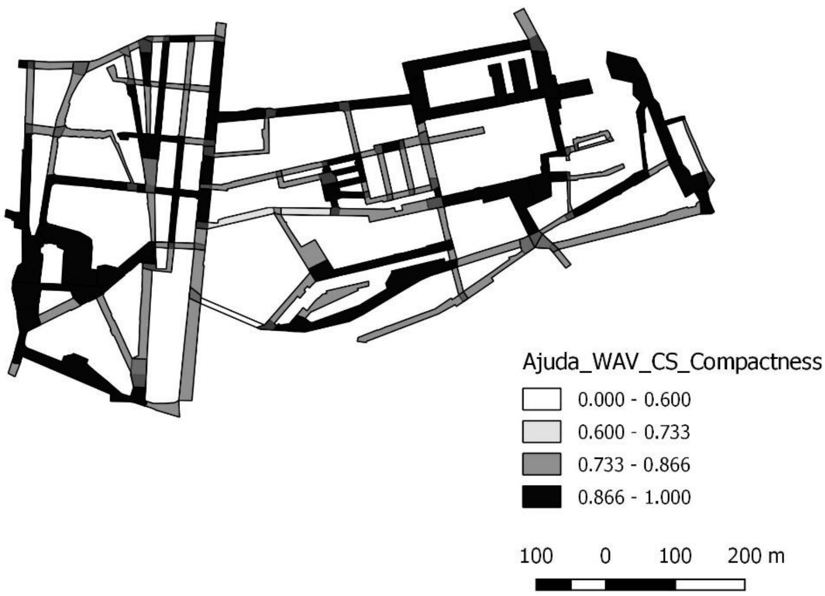
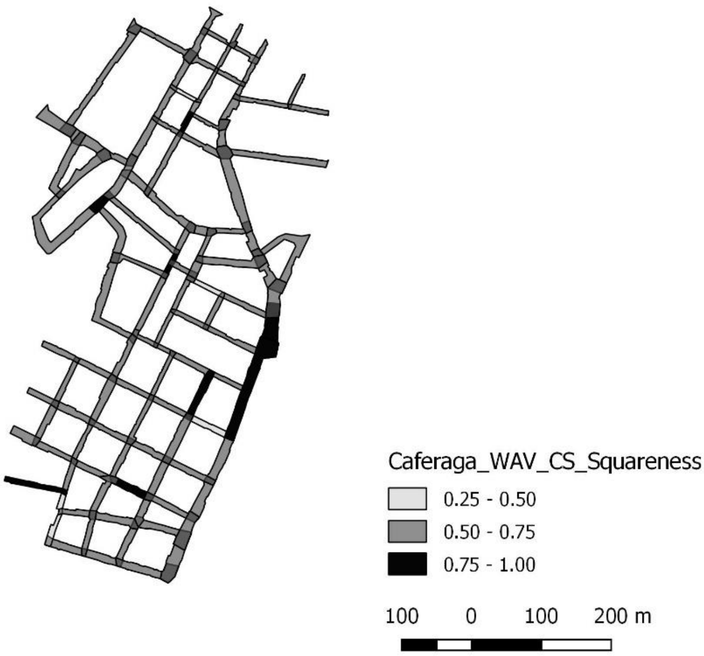


Figure C.36 : Lisbon WAv of Convex-Void Compactness values.



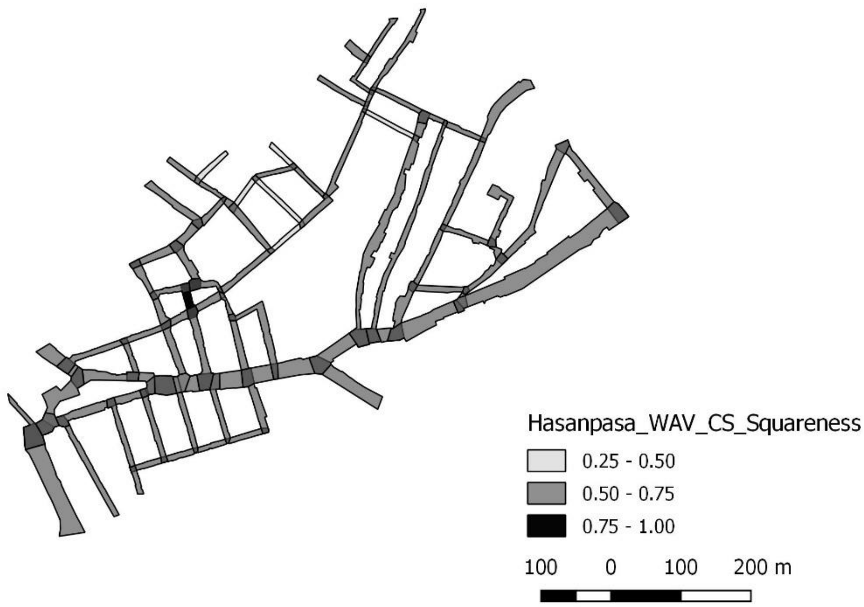
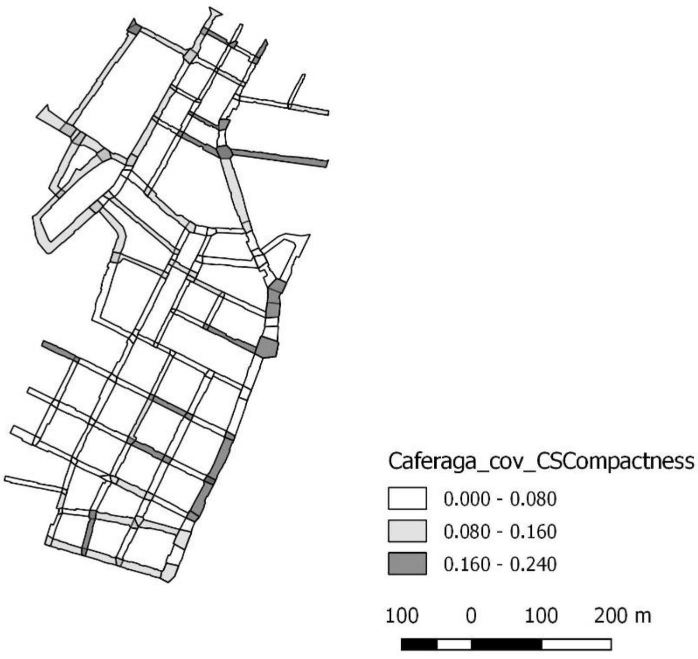


Figure C.37 : Istanbul WAv of Convex Space Squareness values.

Figure C.38 : Lisbon WAv of Convex Space Squareness values.



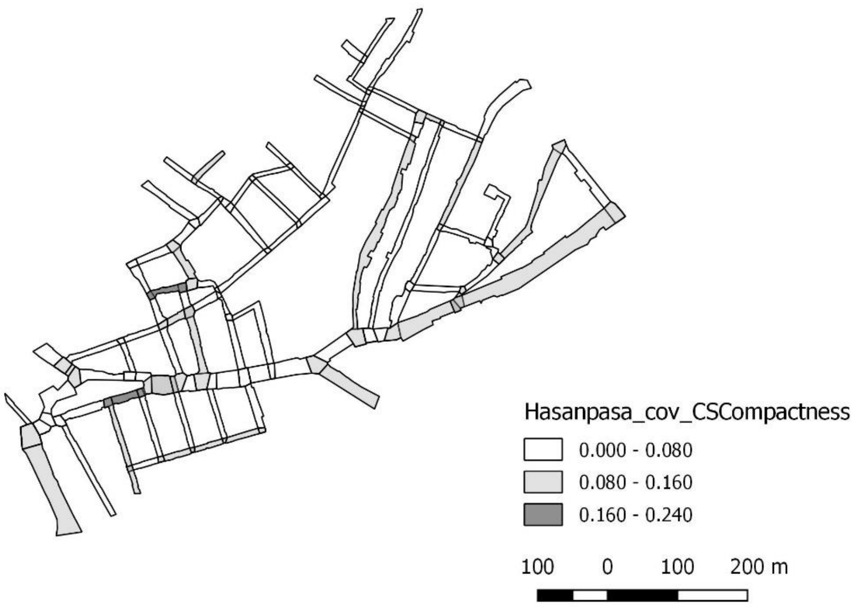


Figure C.39 : Istanbul Cov of Convex Space Compactness values.

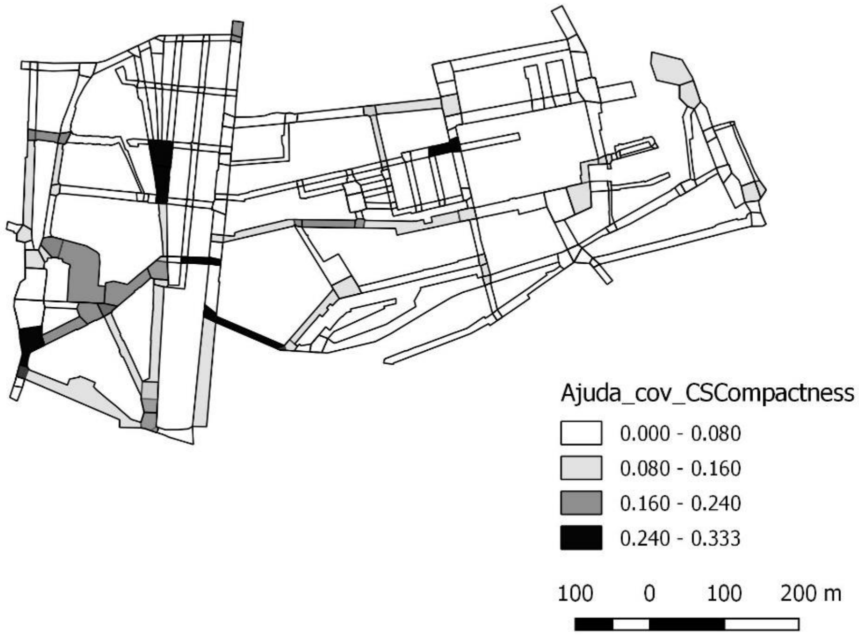
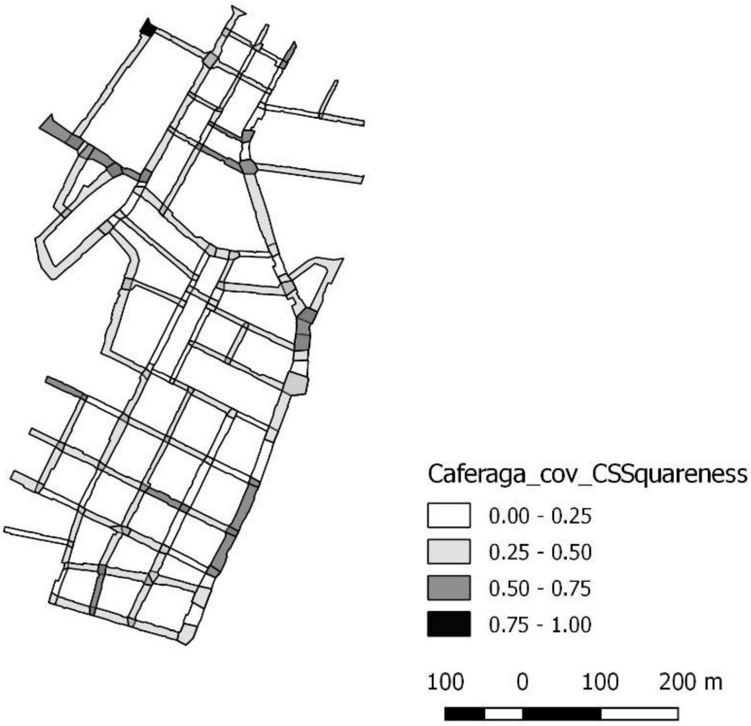


Figure C.40 : Lisbon Cov of Convex Space Compactness values.



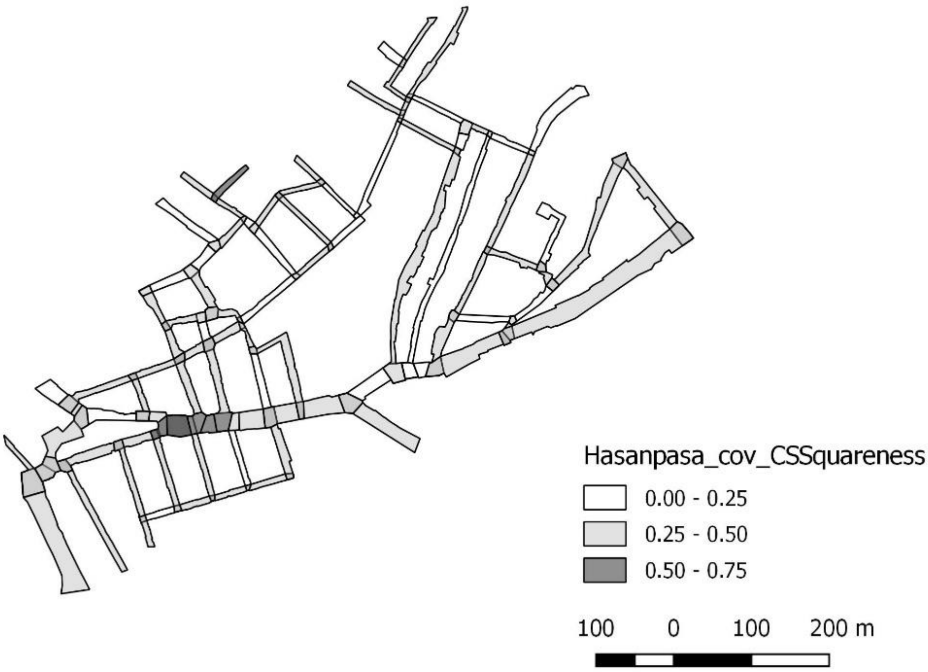
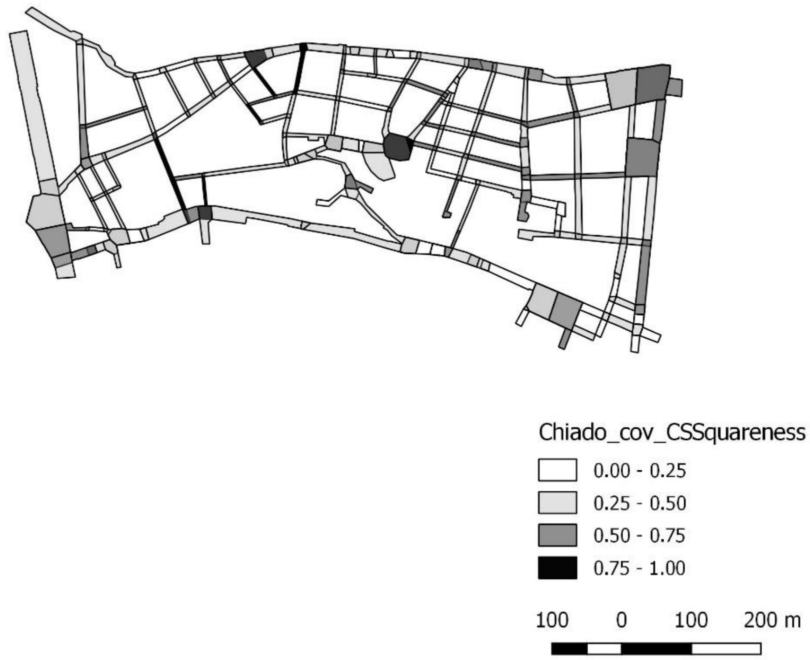


Figure C.41 : Istanbul Cov of Convex Space Squareness values**.**



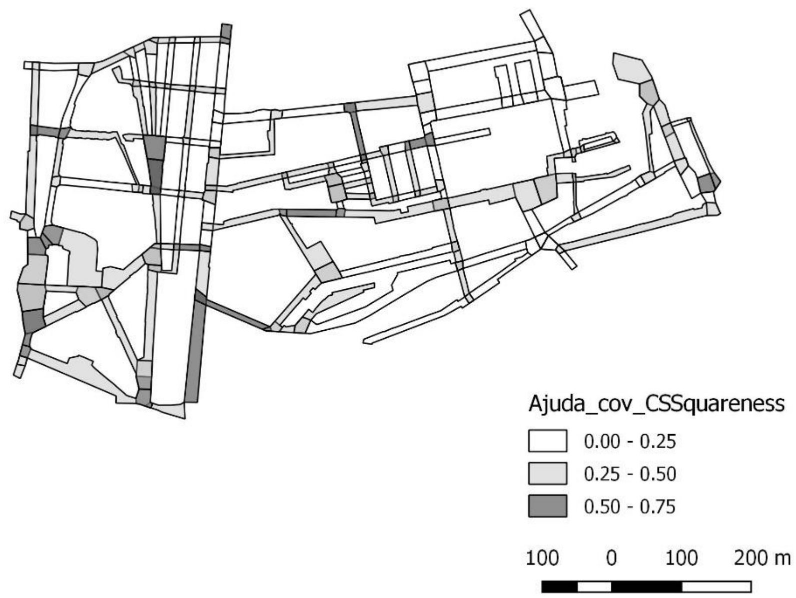


Figure C.42 : Lisbon Cov of Convex Space Squareness values.

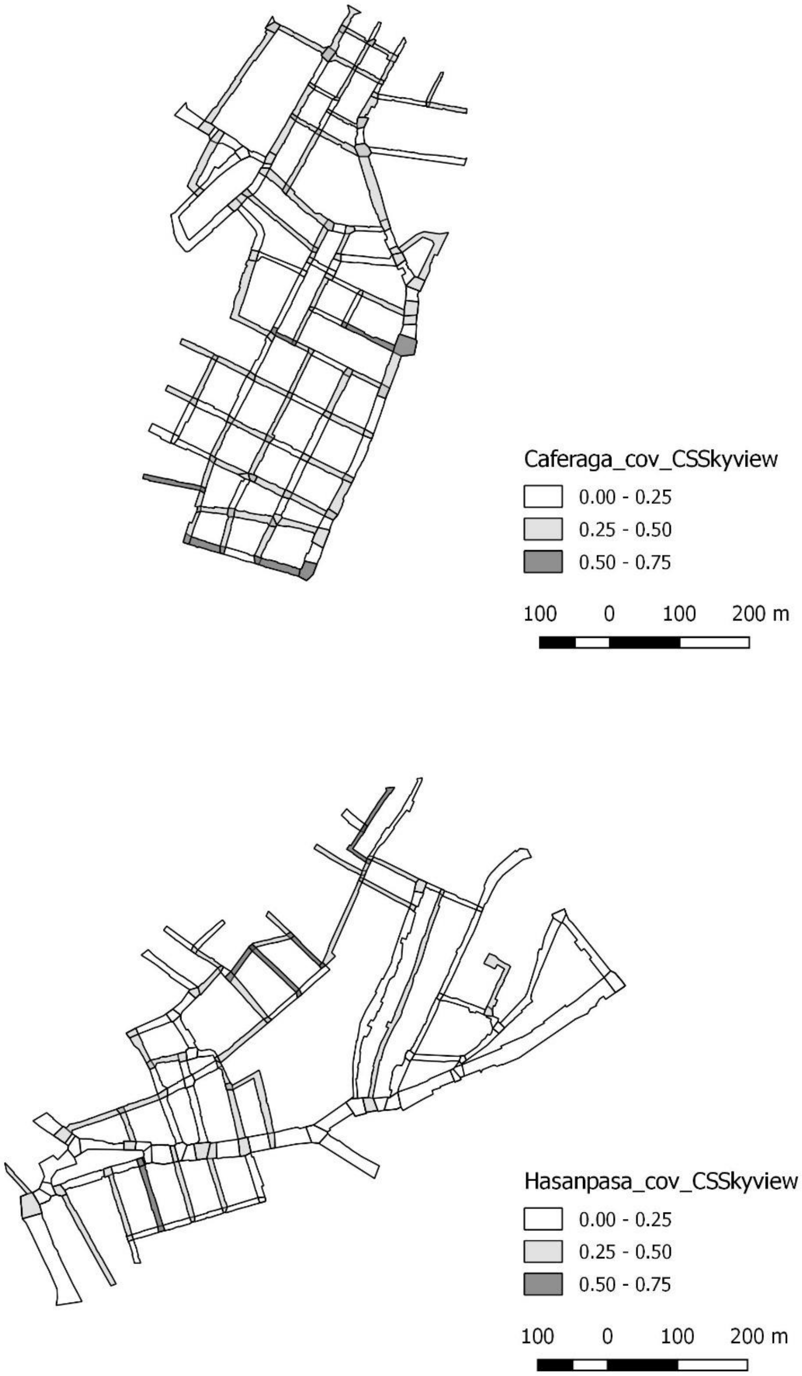
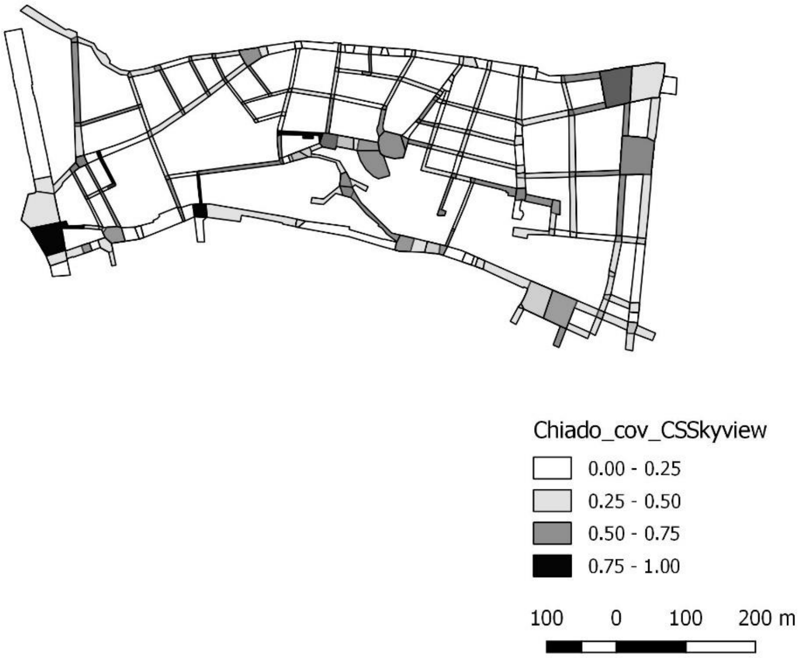


Figure C.43 : Istanbul Cov of Convex Space sky view factor values.



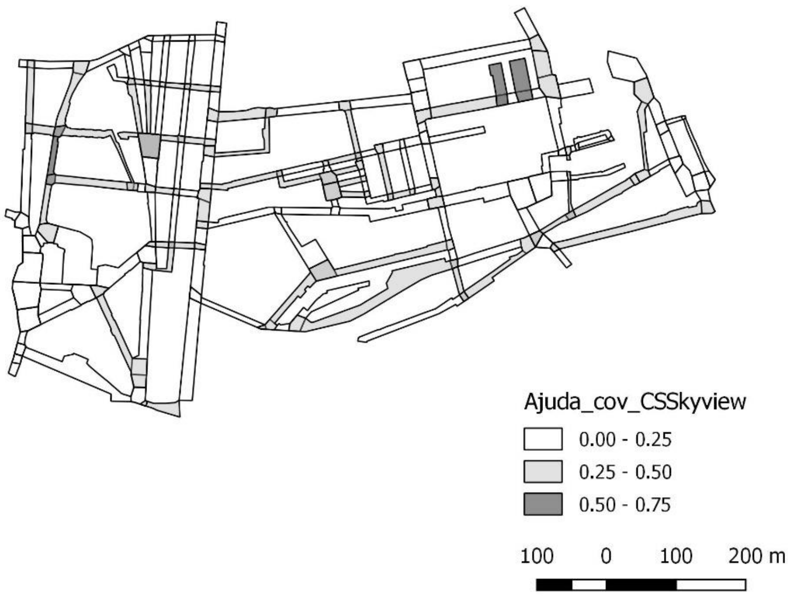
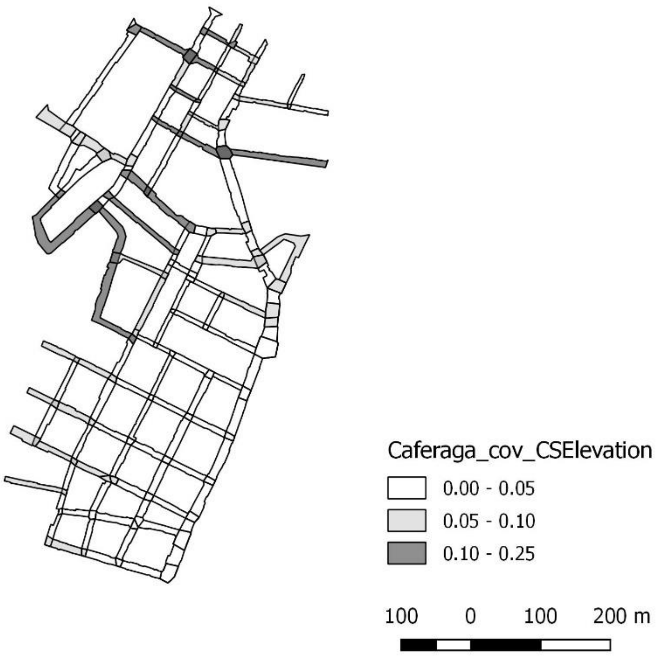


Figure C.44 : Lisbon Cov of Convex Space sky view factor values.



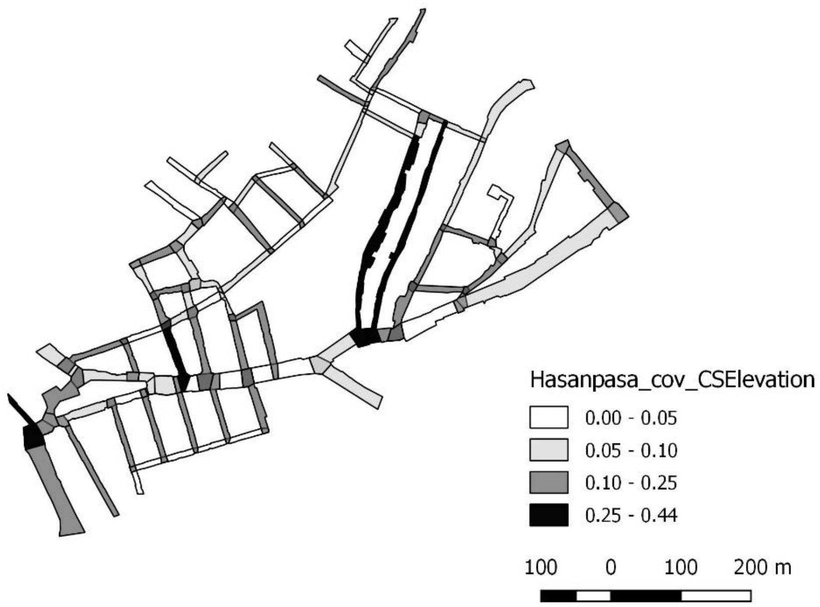
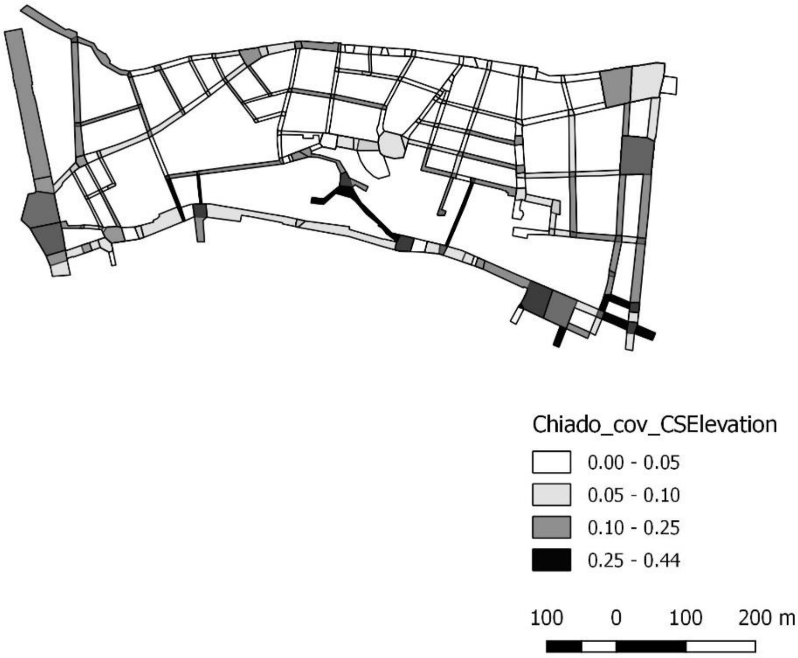


Figure C.45 : Istanbul Cov of Convex Space elevation values.



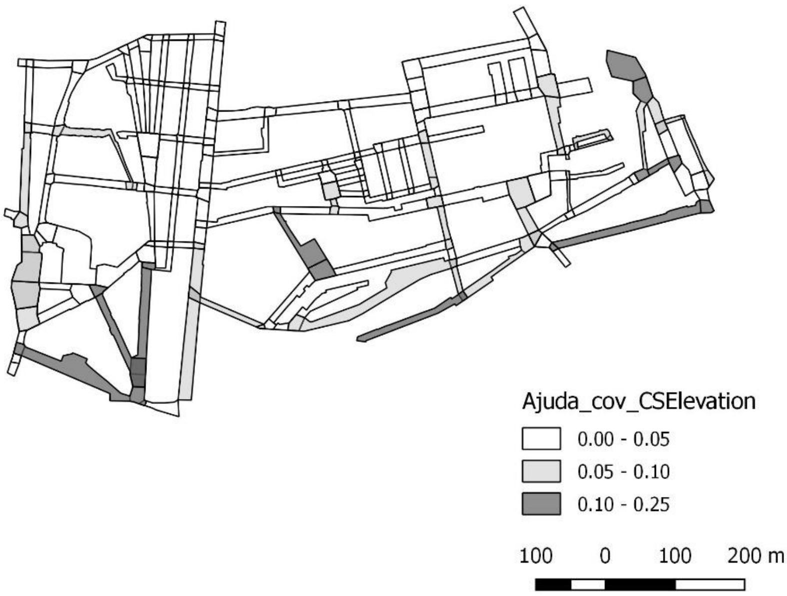
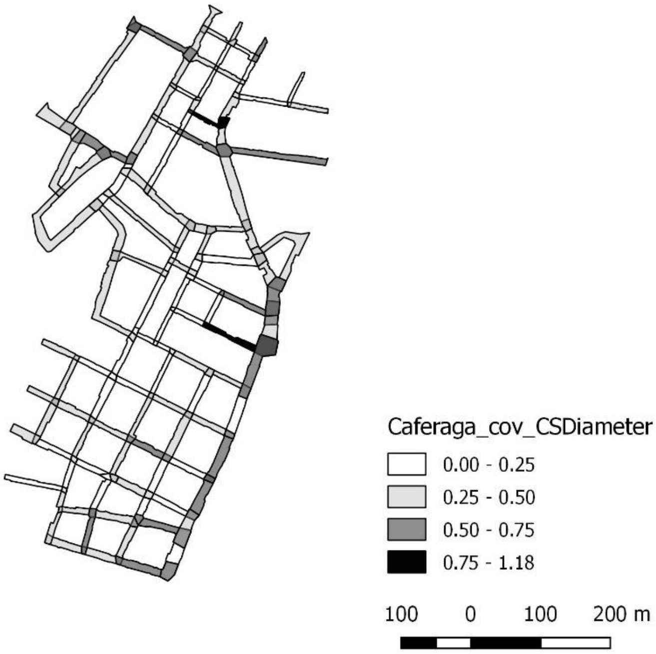


Figure C.46 : Lisbon Cov of Convex Space elevation values.



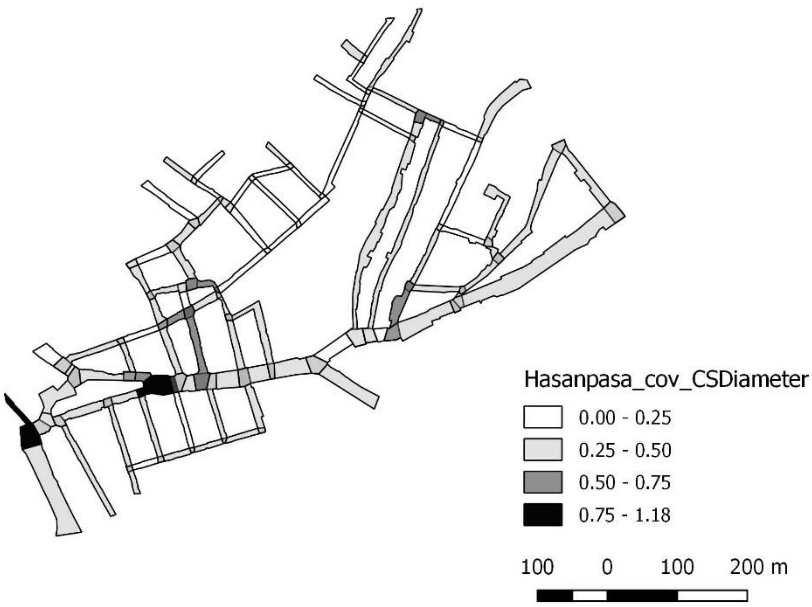


Figure C.47 : Istanbul Cov of Convex Space diameter values.

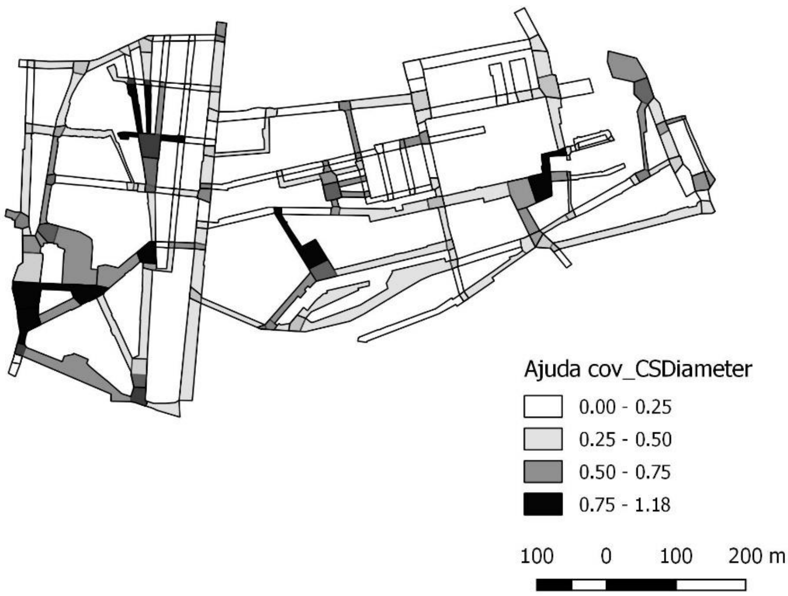
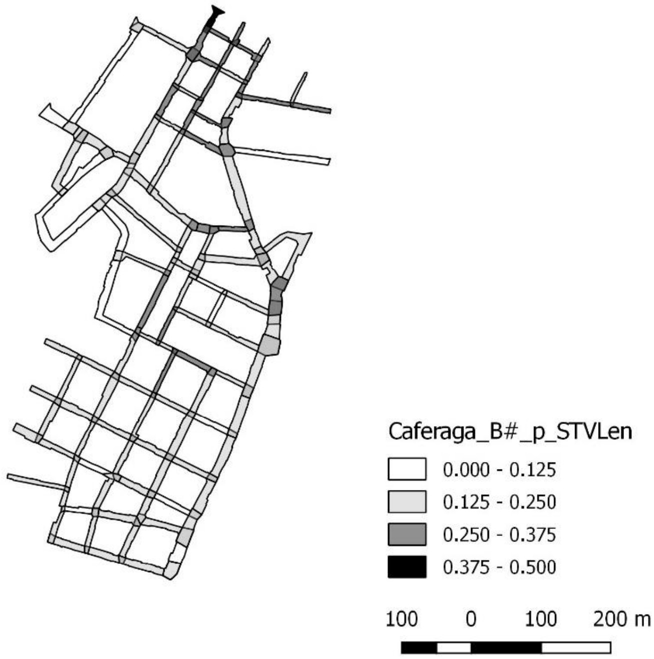


Figure C.48 : Lisbon Cov of Convex Space diameter values.

APPENDIX D



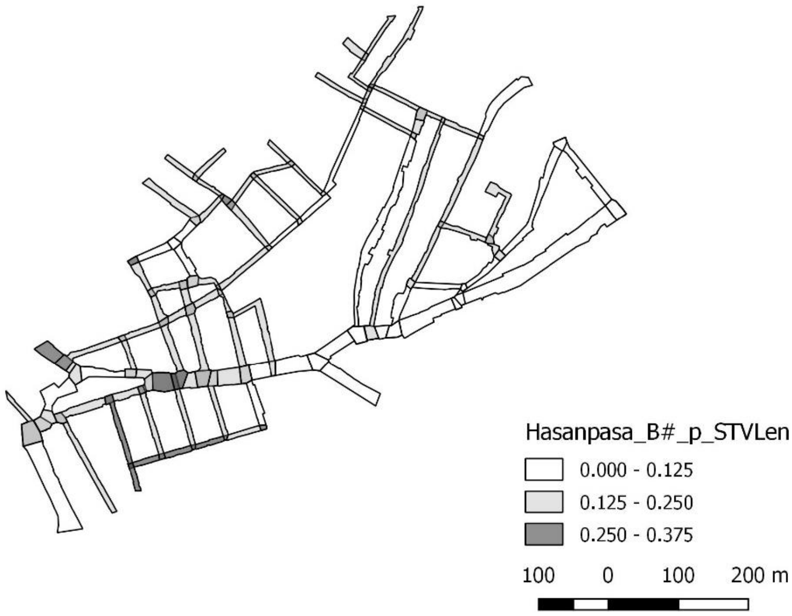
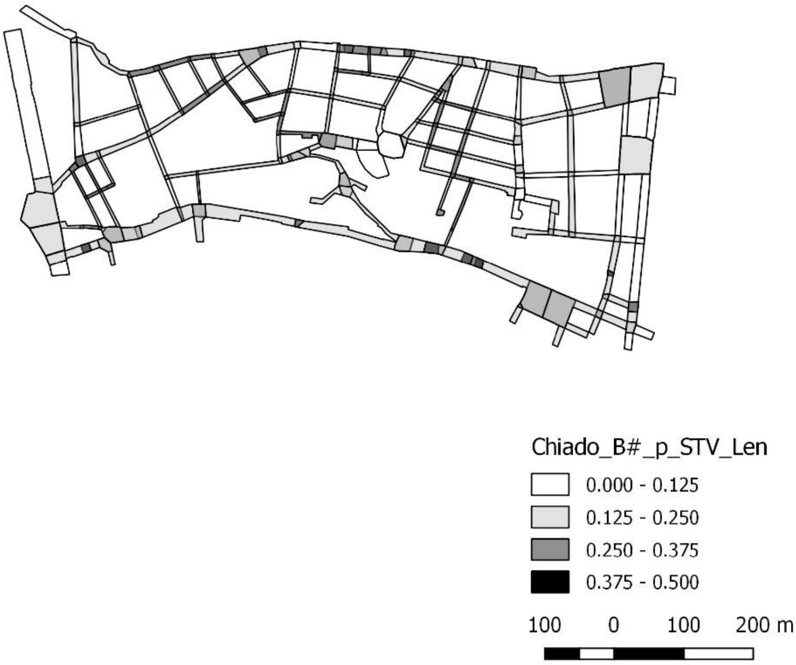


Figure D.1 : Istanbul number of buildings per STV length.



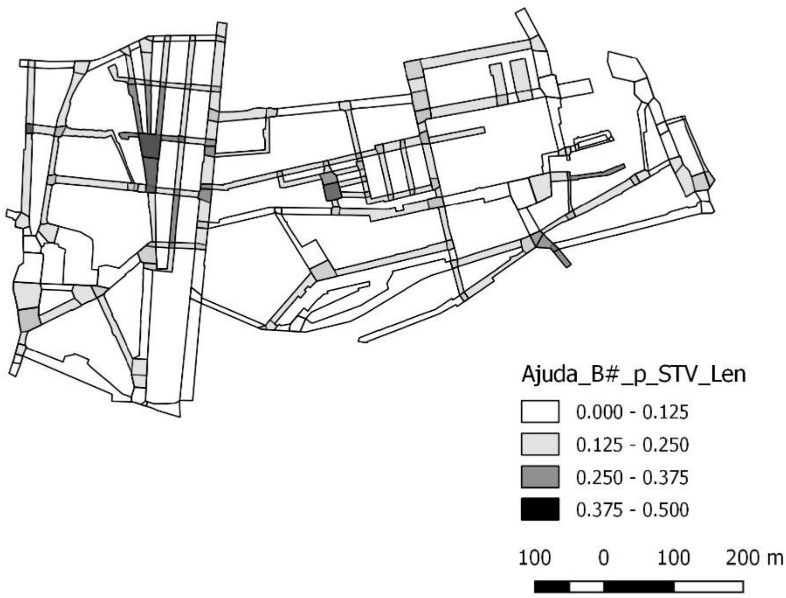
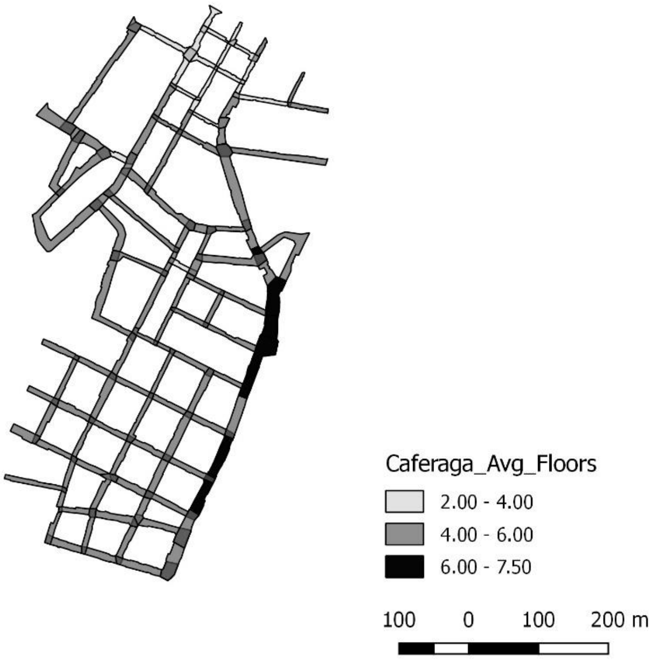


Figure D.2 : Lisbon number of buildings per STV length.



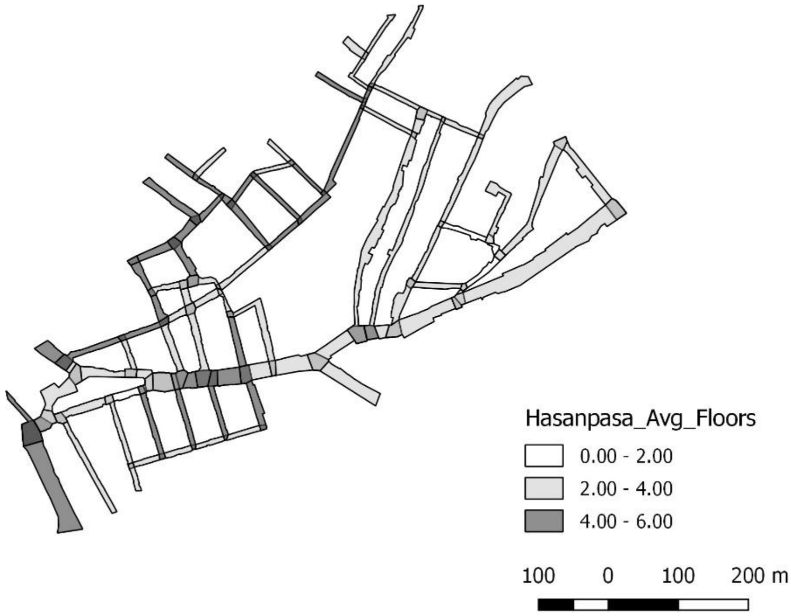


Figure D.3 : Istanbul average number of floors per building per STV.

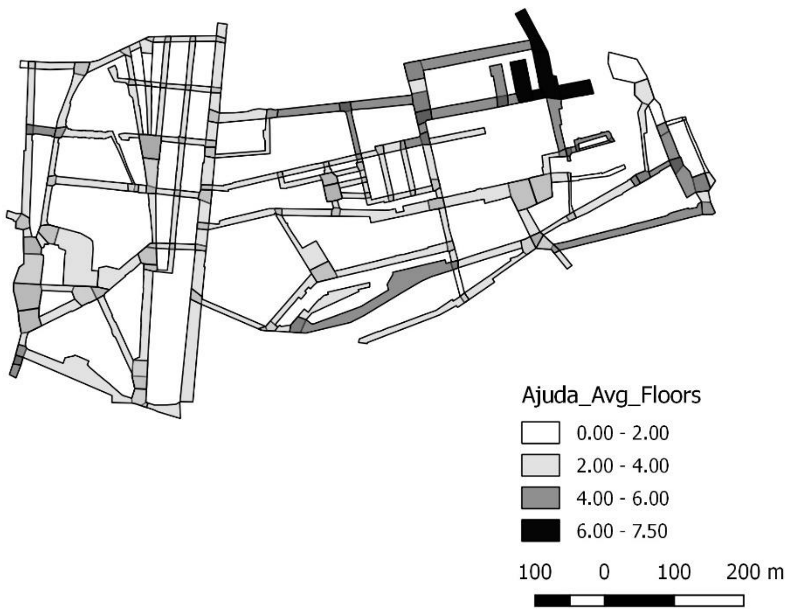
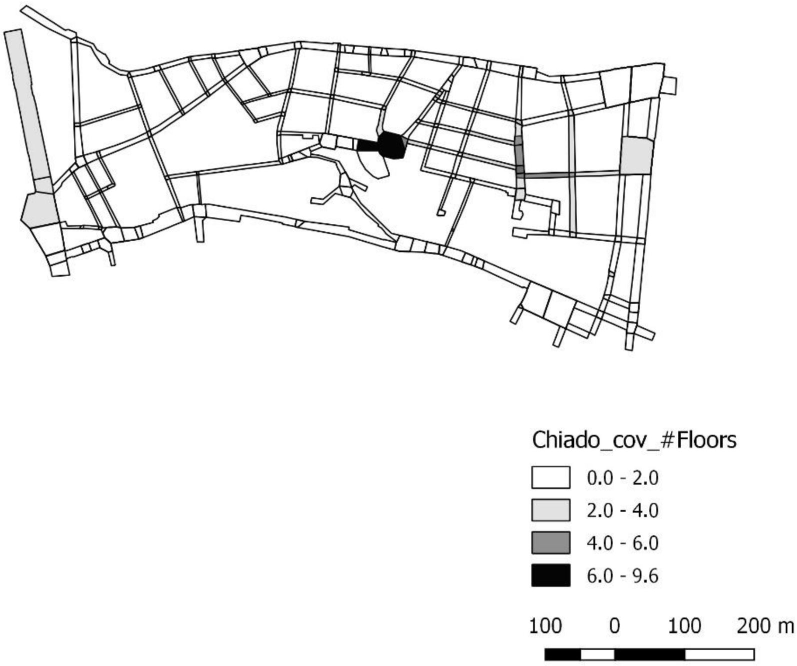


Figure D.4 : Lisbon average number of floors per building per STV.

Figure D.5 : Istanbul Cov of number of floors per building per STV.



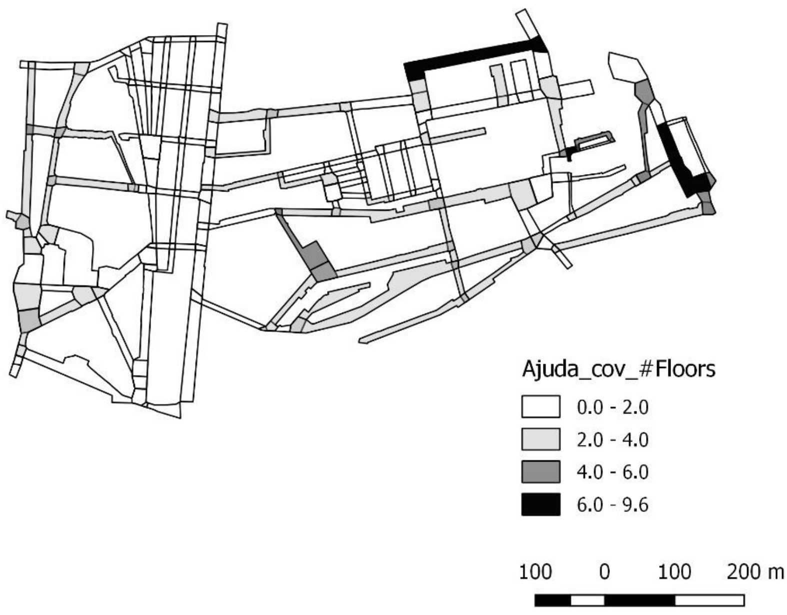
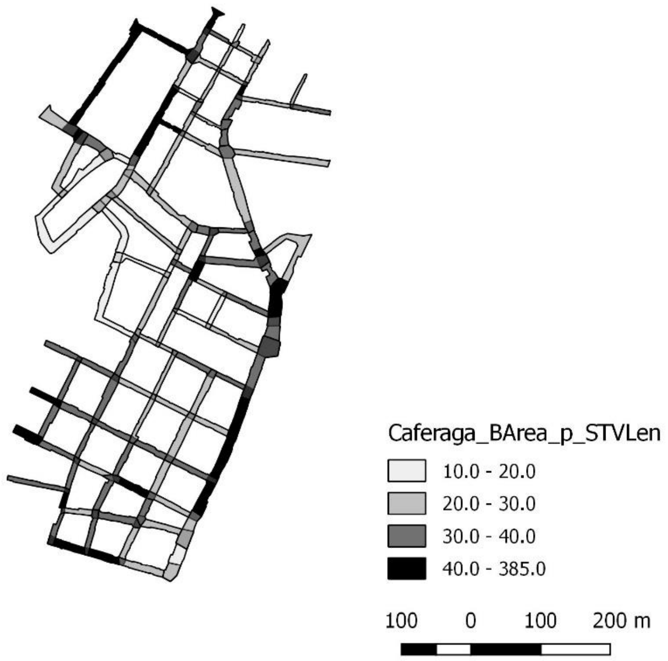


Figure D.6 : Lisbon Cov of number of floors per building per STV.



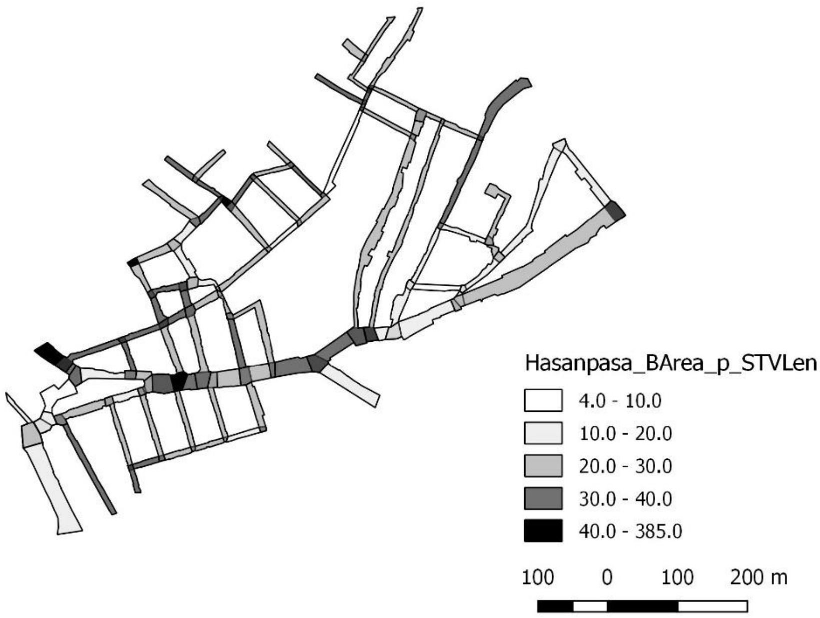


Figure D.7 : Istanbul total building footprint area per STV length.

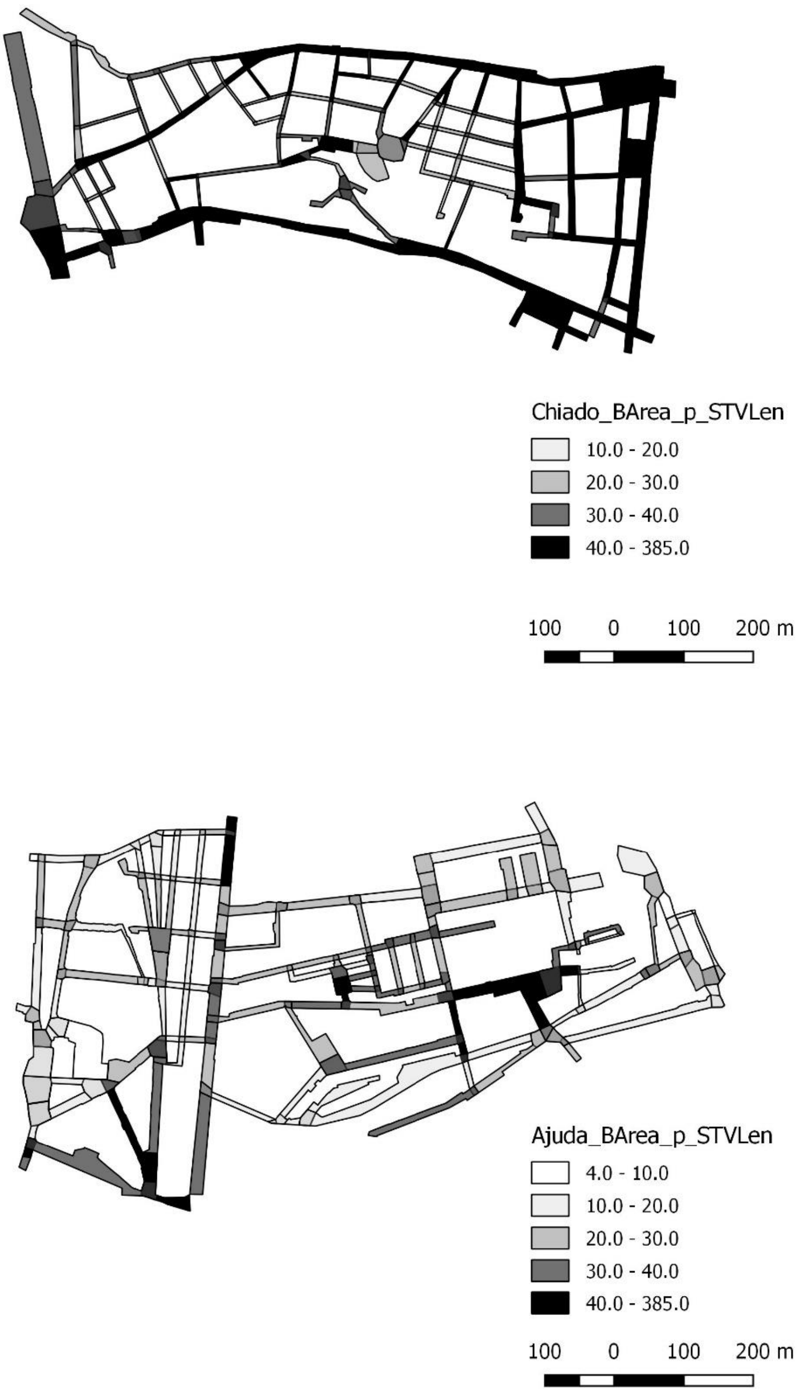


Figure D.8 : Lisbon total building footprint area per STV length.

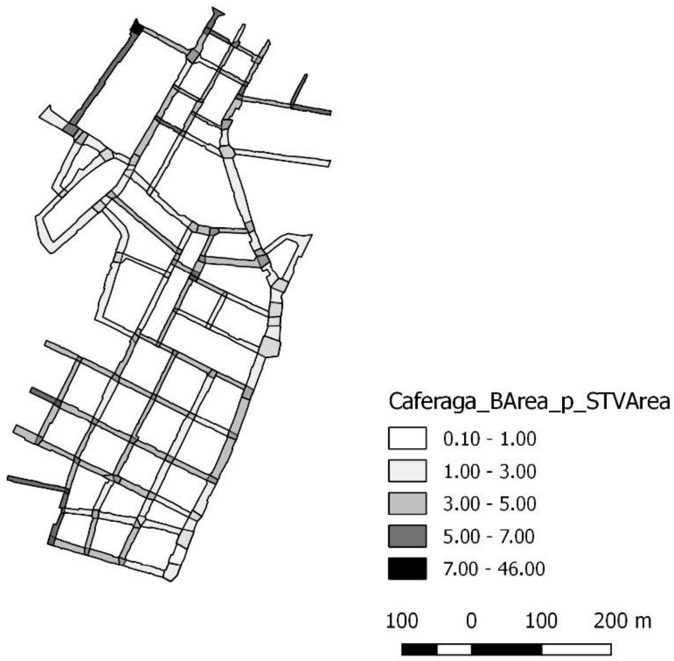


Figure D.9 : Istanbul total building footprint area per STV area.

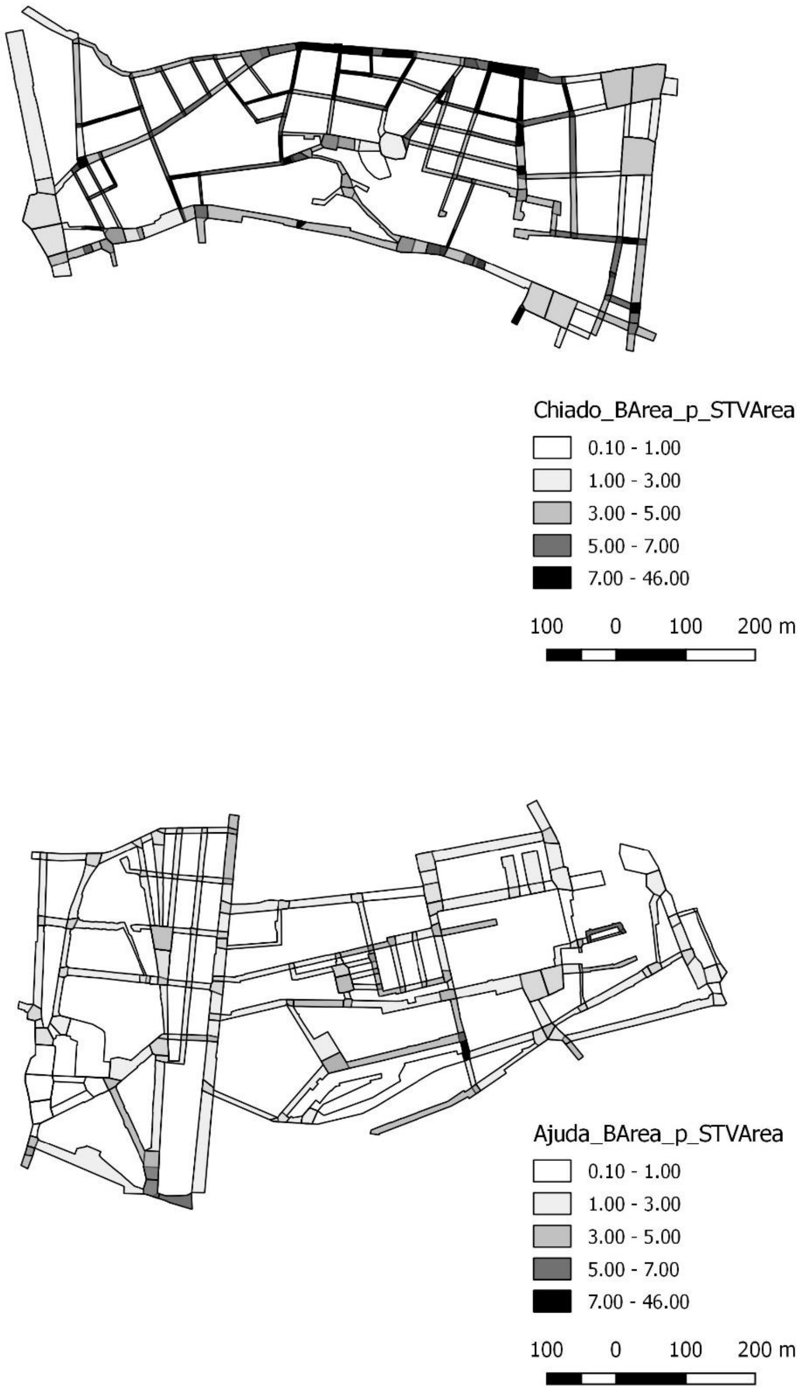
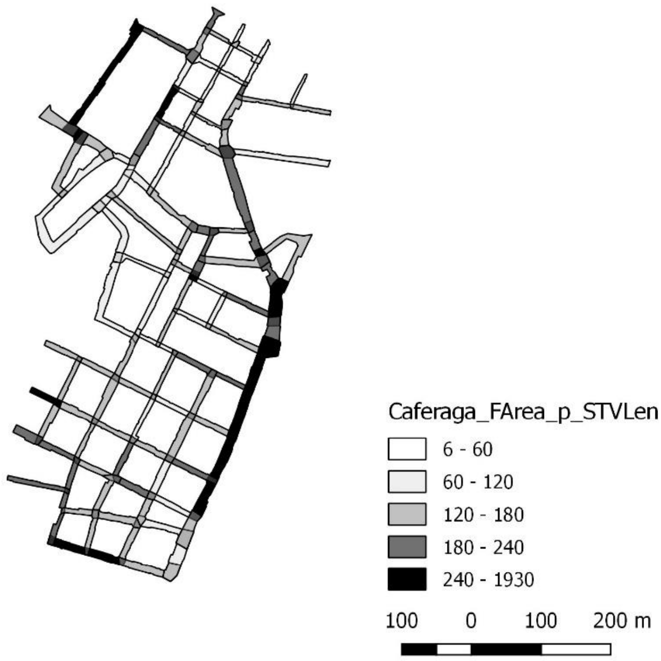


Figure D.10 : Lisbon total building footprint area per STV area.



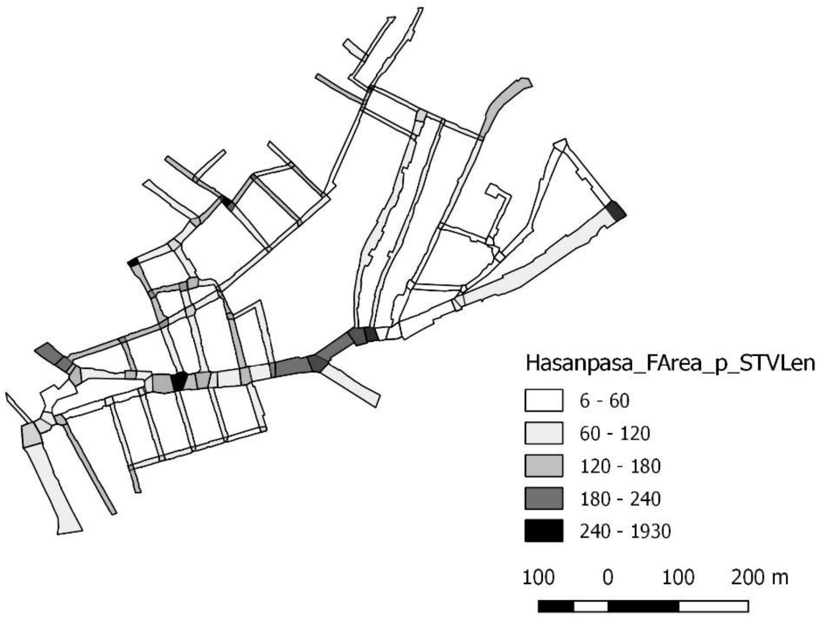
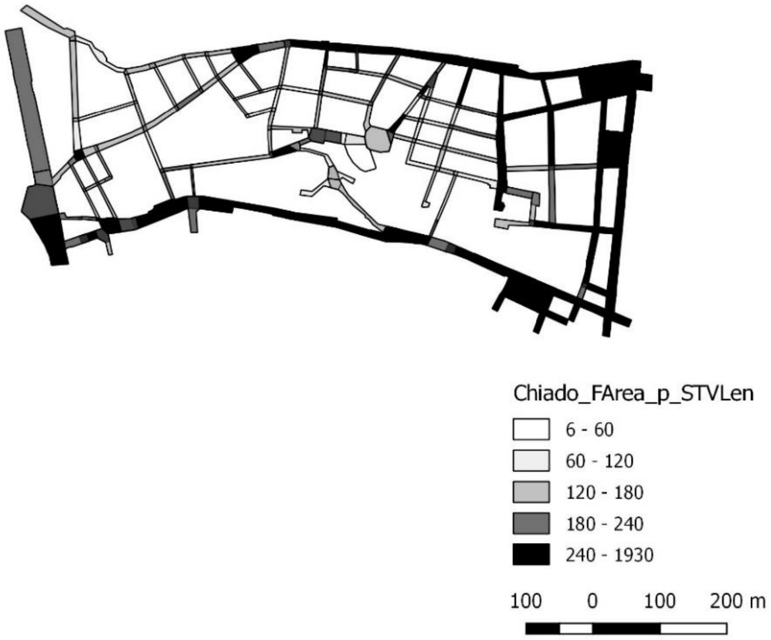


Figure D.11 : Istanbul total building floor area per STV length.



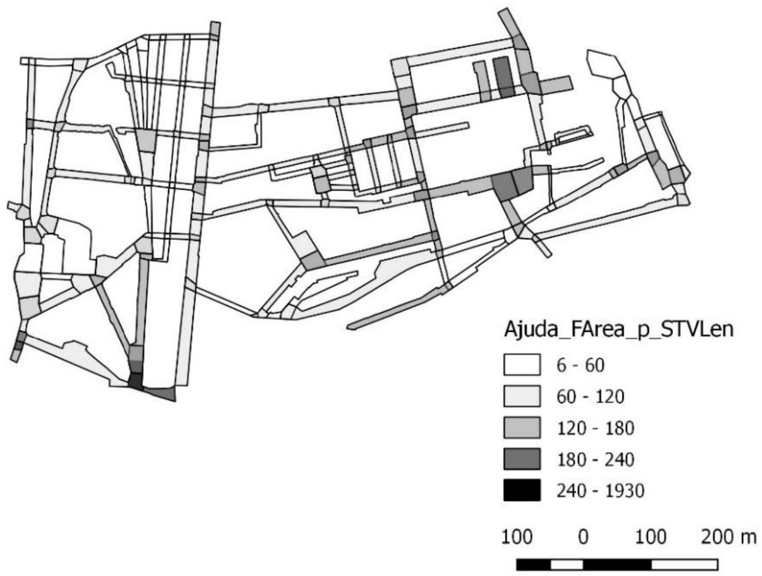
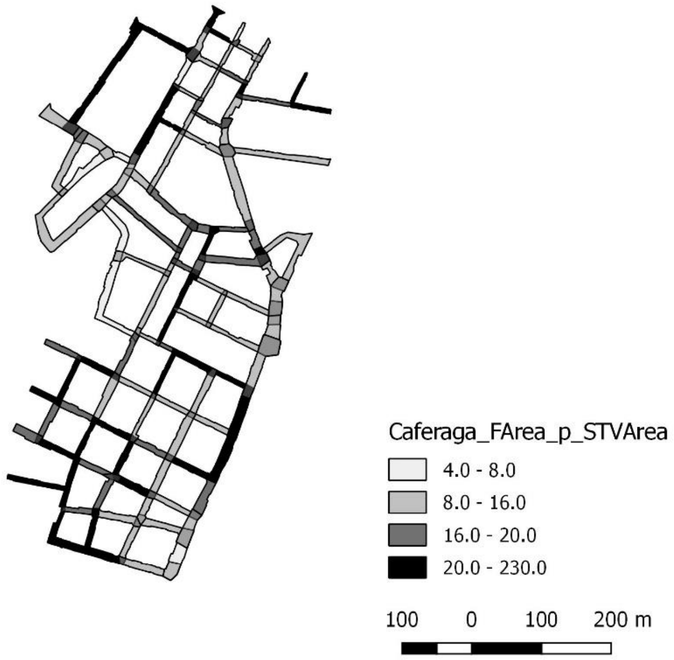


Figure D.12 : Lisbon total building floor area per STV length.



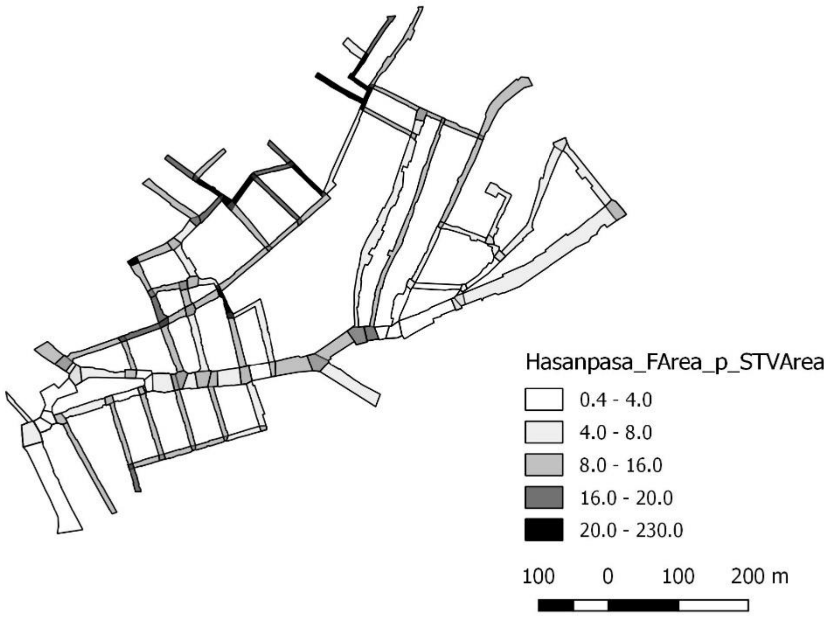
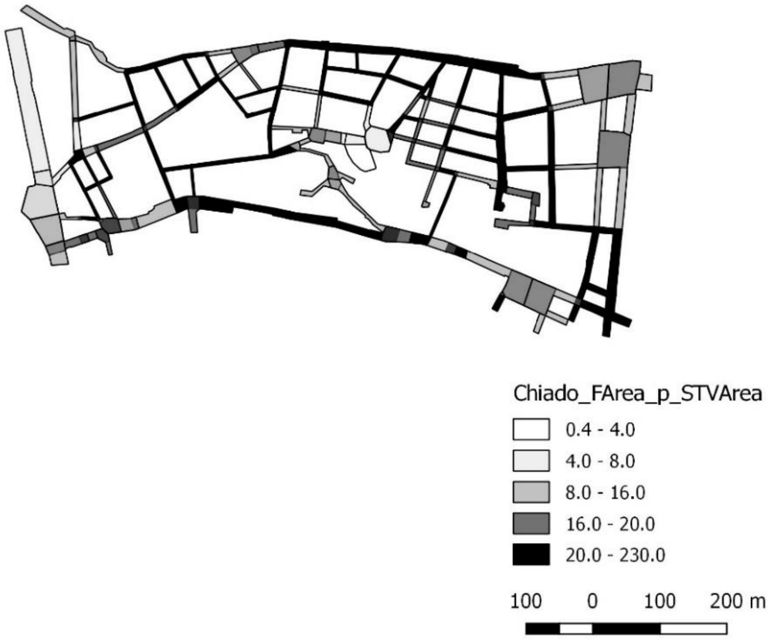


Figure D.13 : Istanbul total building floor area per STV area.



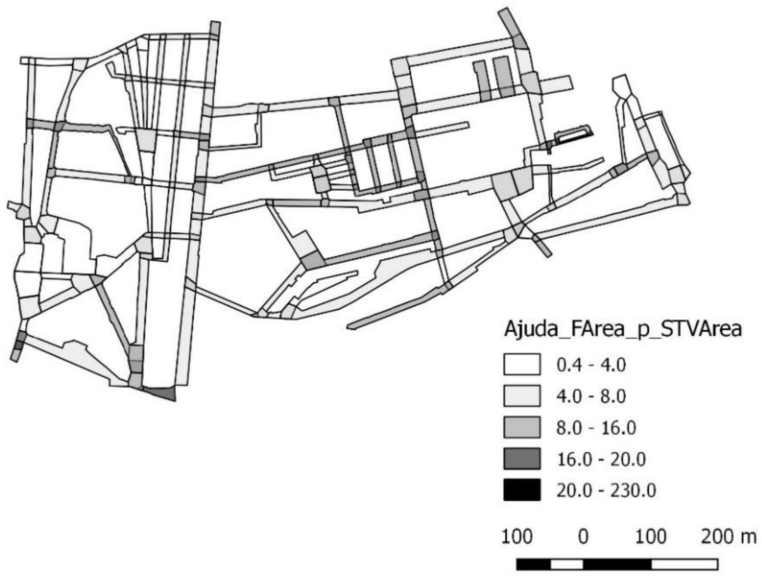


Figure D.14 : Lisbon total building floor area per STV area.

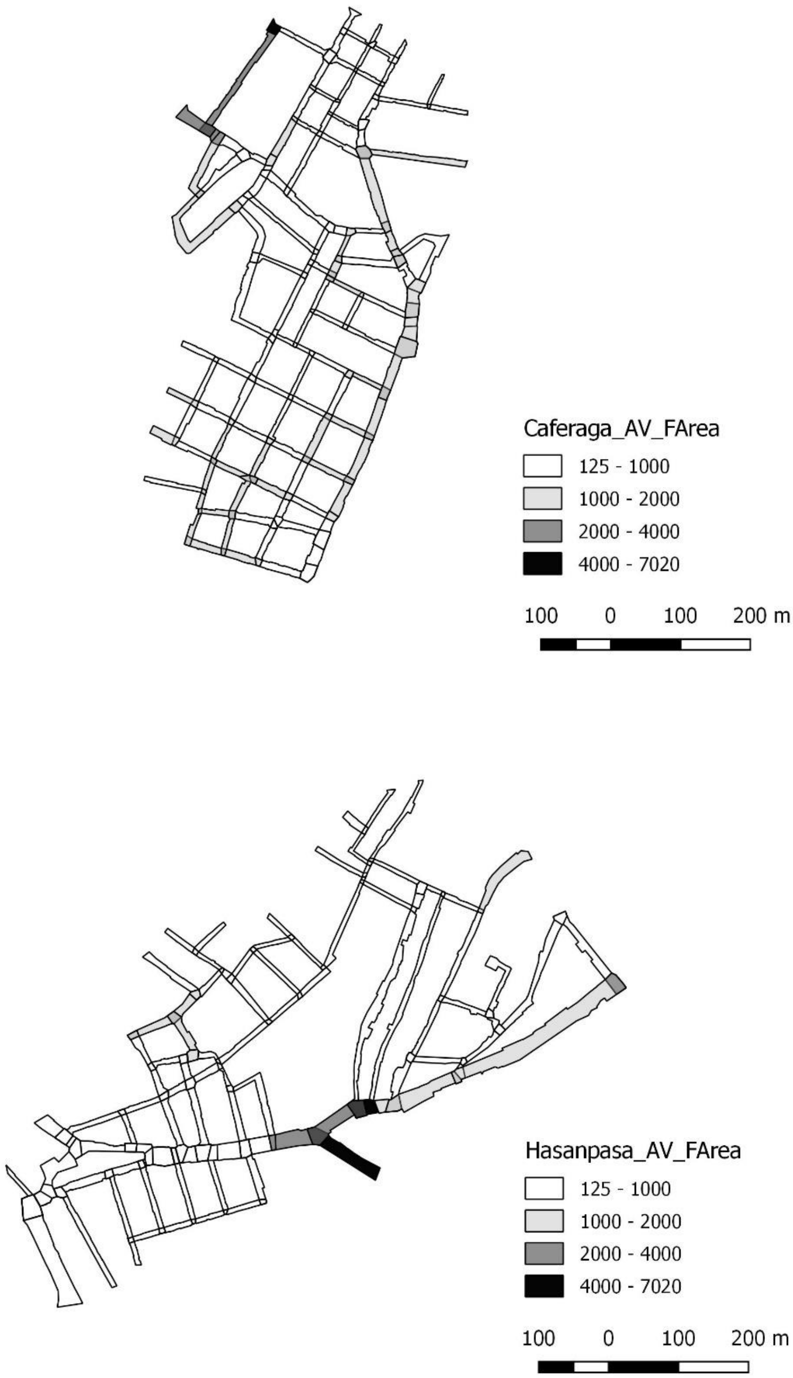


Figure D.15 : Istanbul average floor area per building per STV.

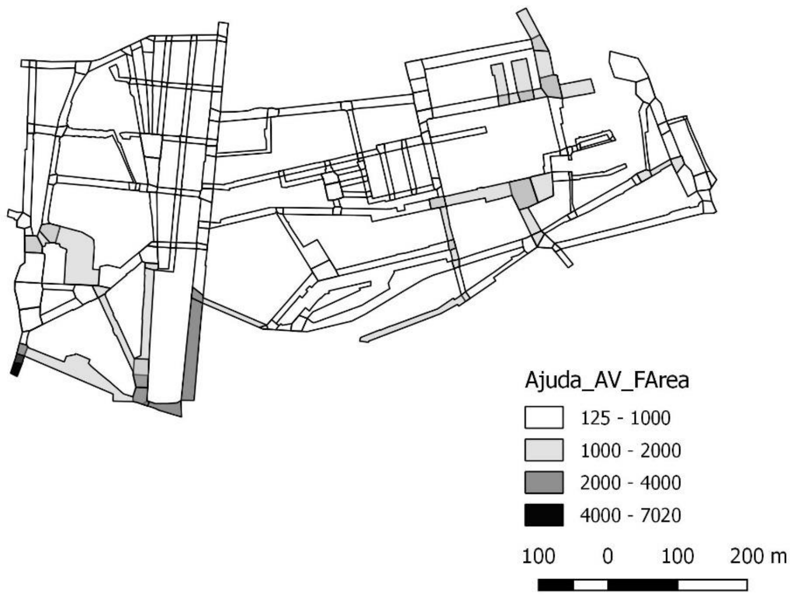
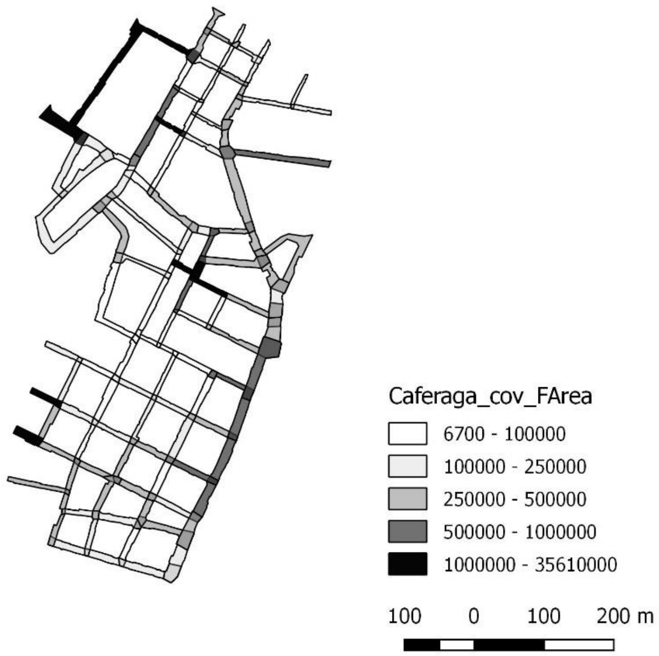


Figure D.16 : Lisbon average floor area per building per STV.



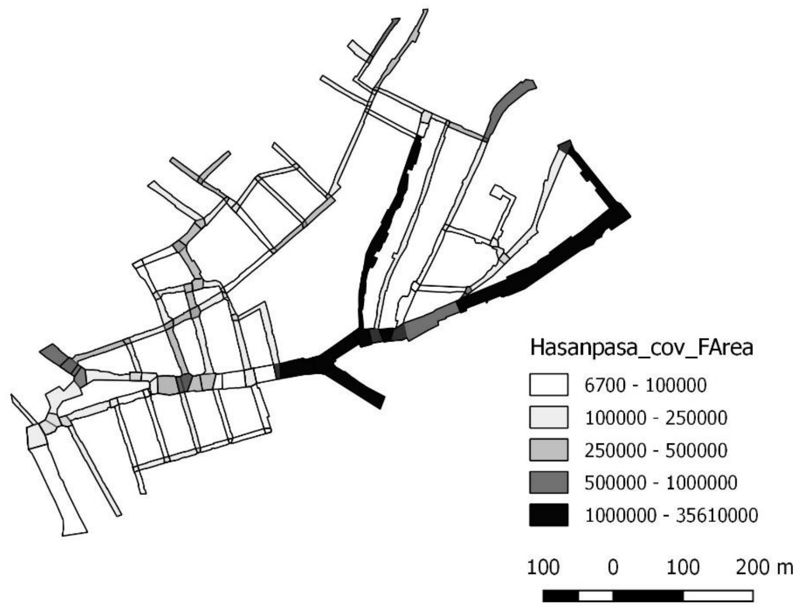
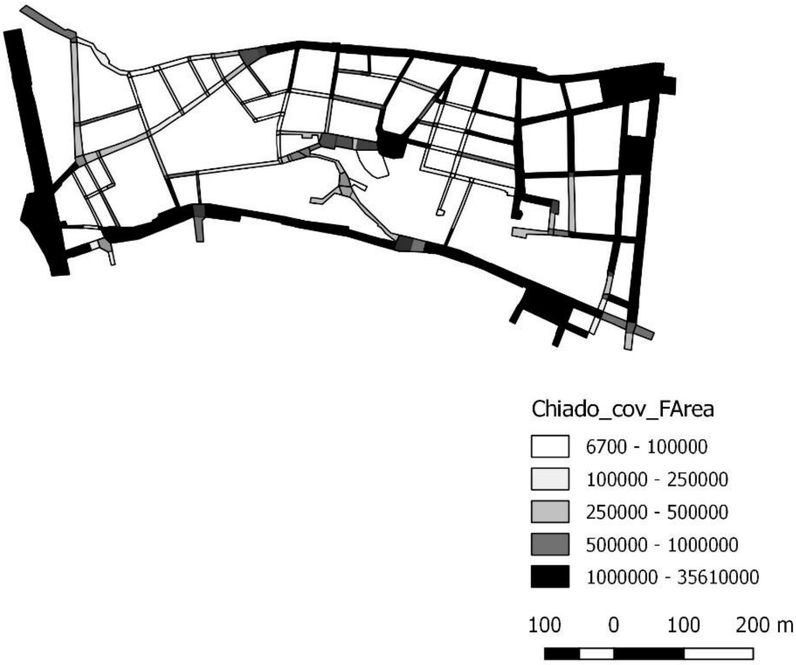


Figure D.17 : Istanbul Cov of floor area per building per STV.



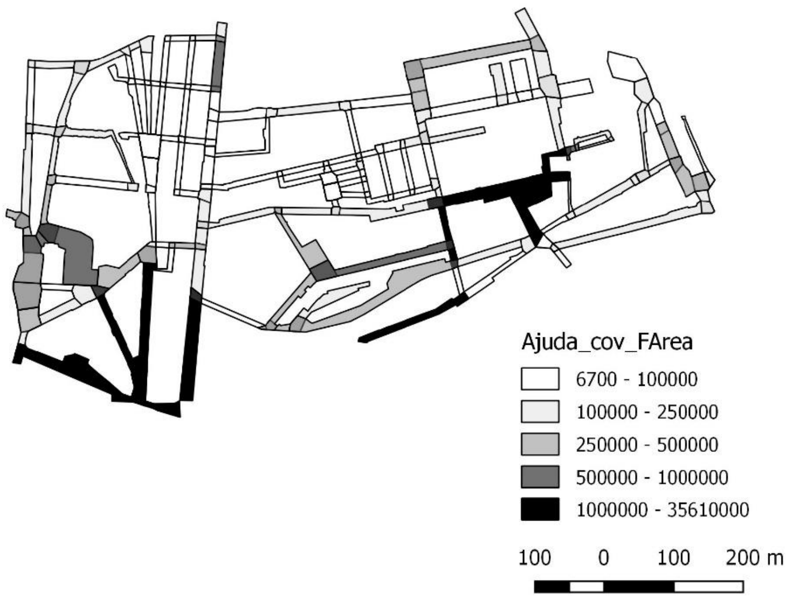
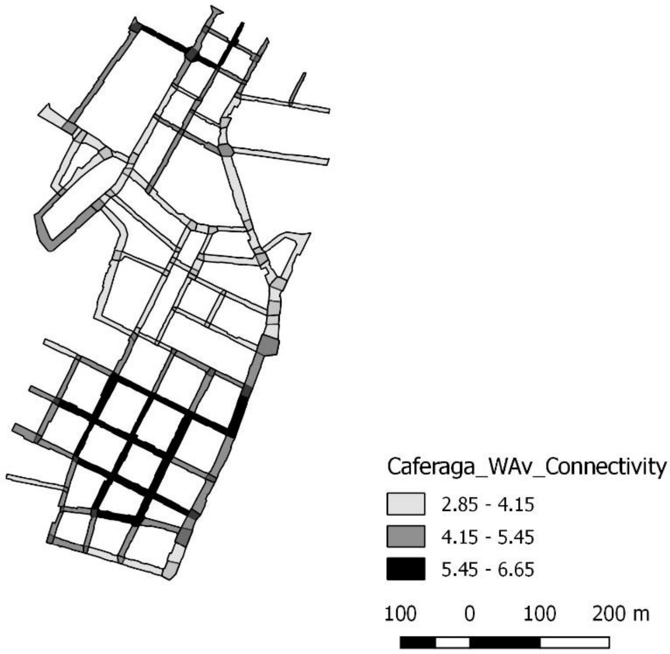


Figure D.18 : Lisbon Cov of floor area per building per STV.

APPENDIX E



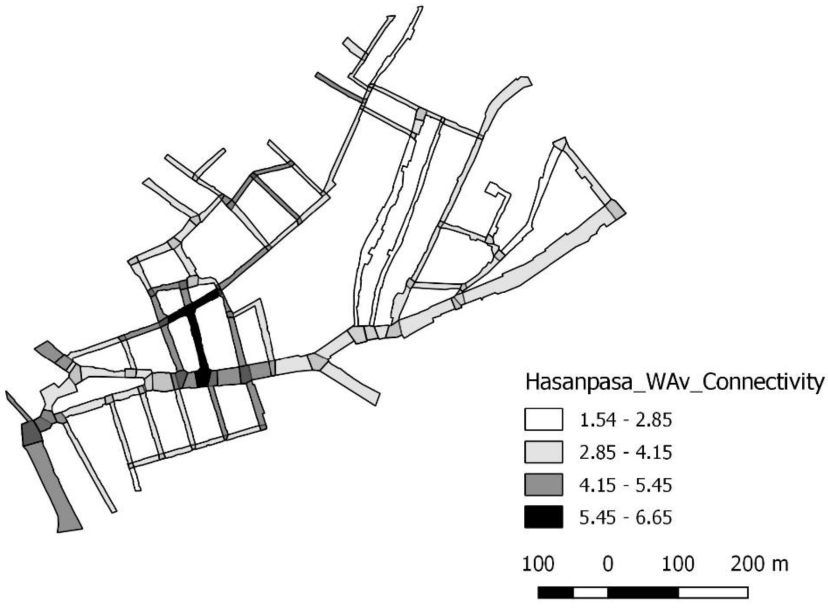
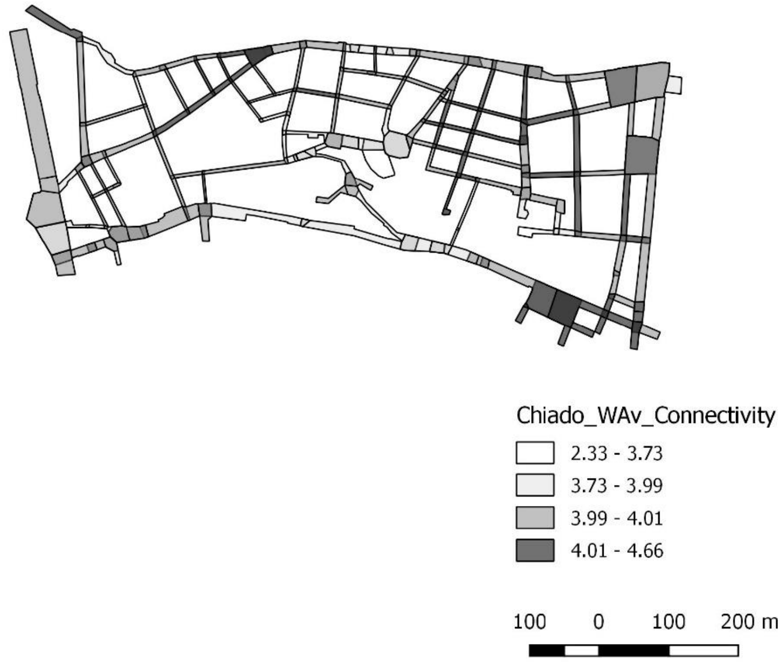


Figure E.1 : Istanbul WAv of Connectivity per street segment per STV.



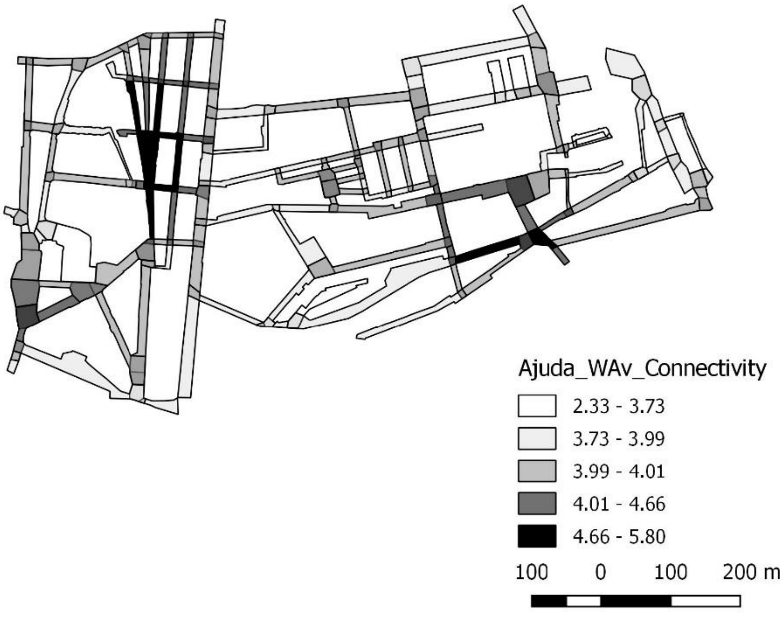
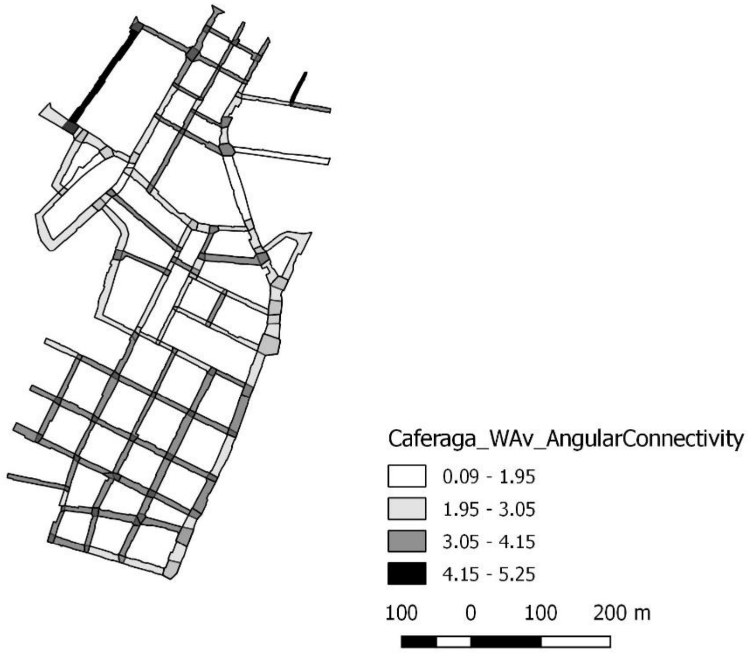


Figure E.2 : Lisbon WAv of Connectivity per street segment per STV.



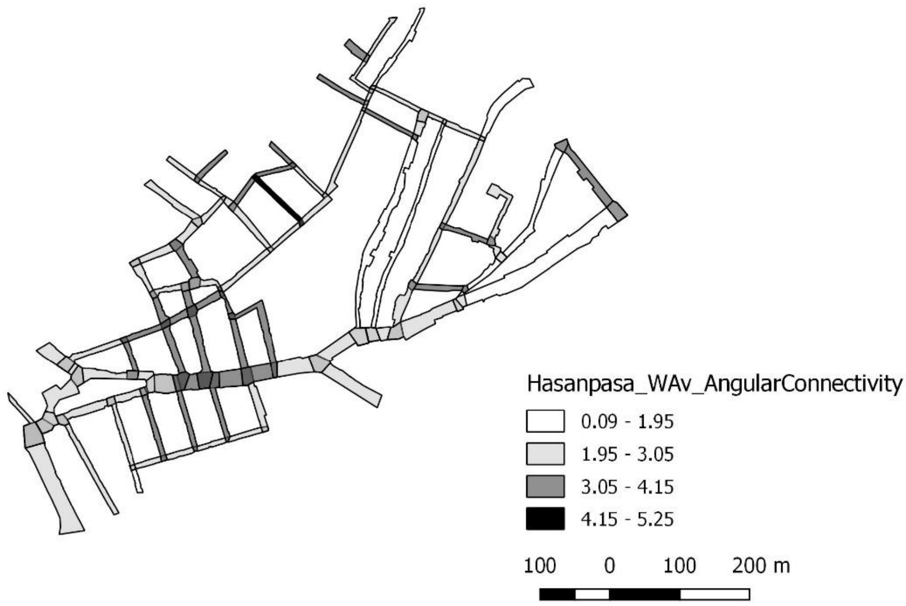


Figure E.3 : Istanbul WAv of Angular Connectivity per street segment per STV.

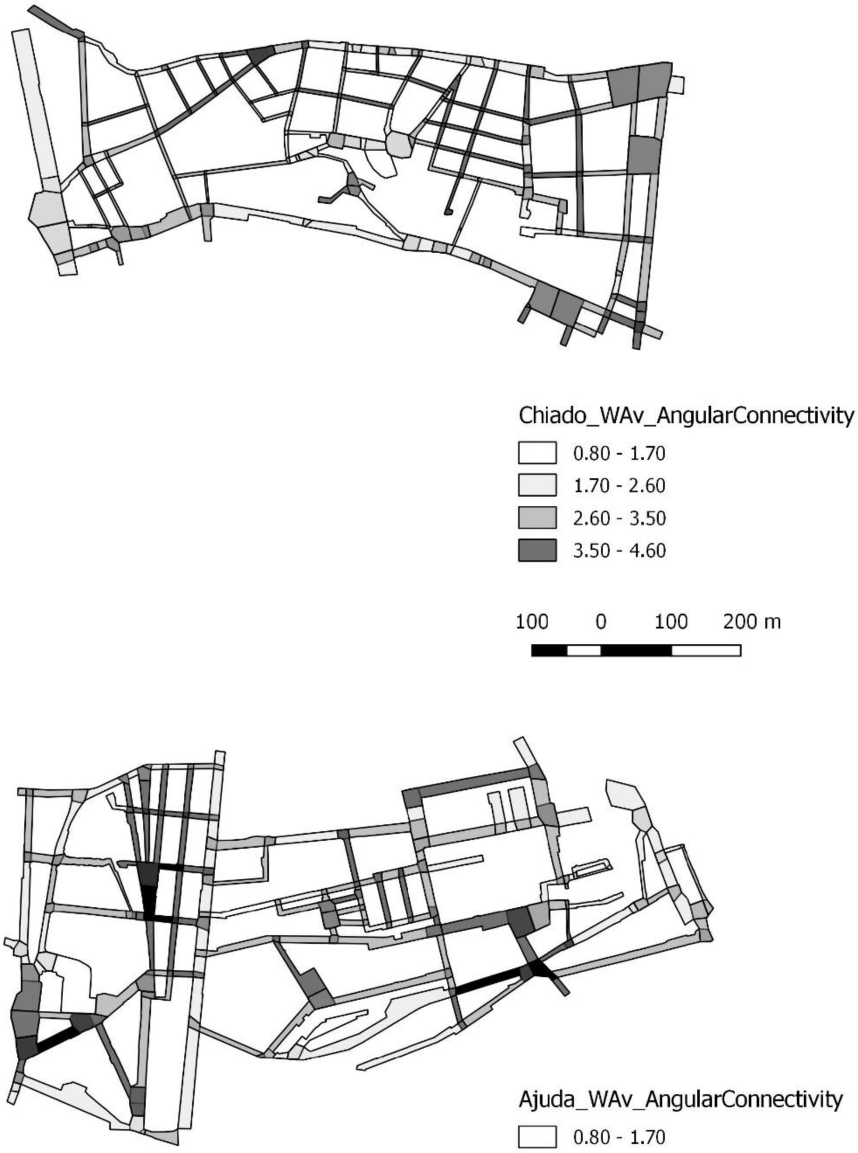


Figure E.4 : Lisbon WAv of Angular Connectivity per street segment per STV.

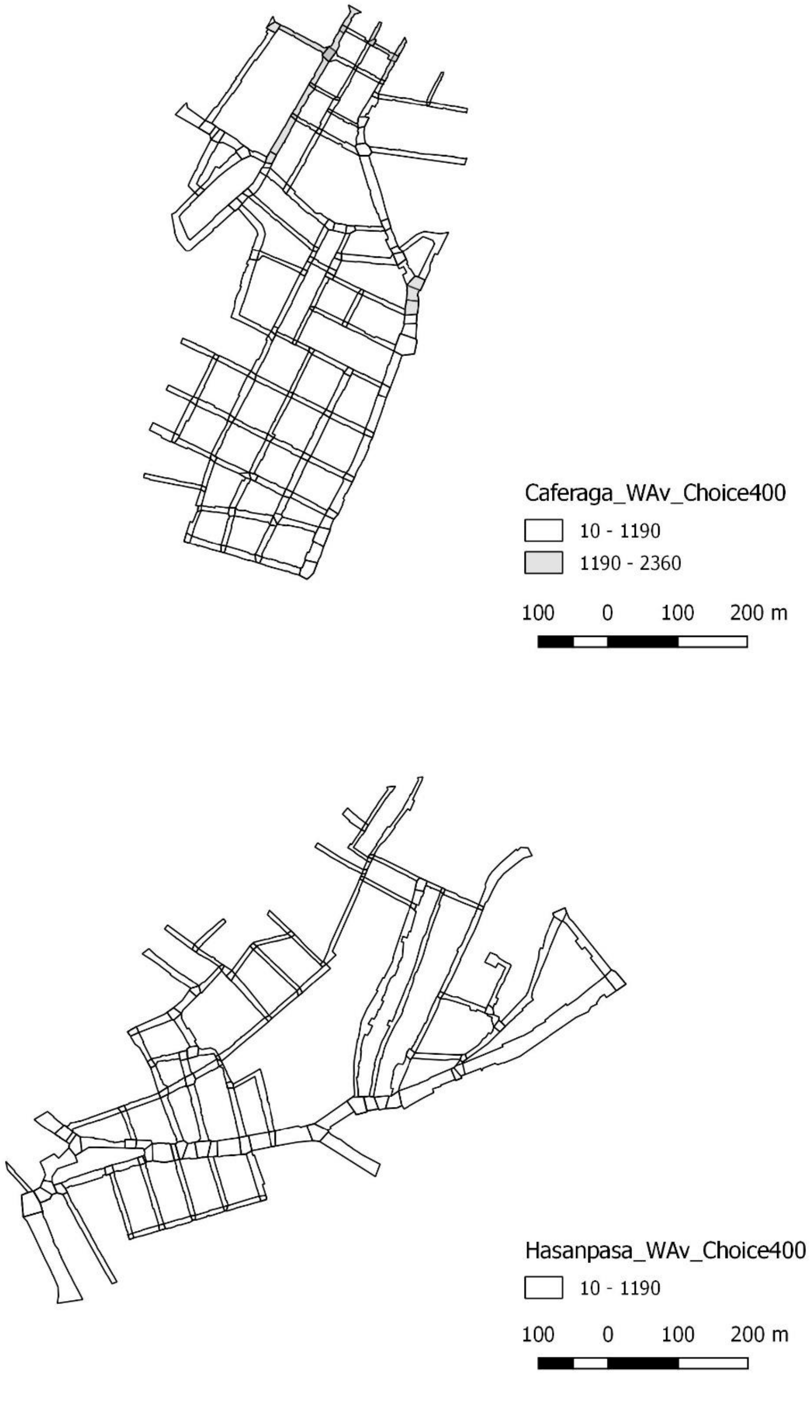


Figure E.5 : Istanbul WAv of Choice for 400m per street segment per STV.

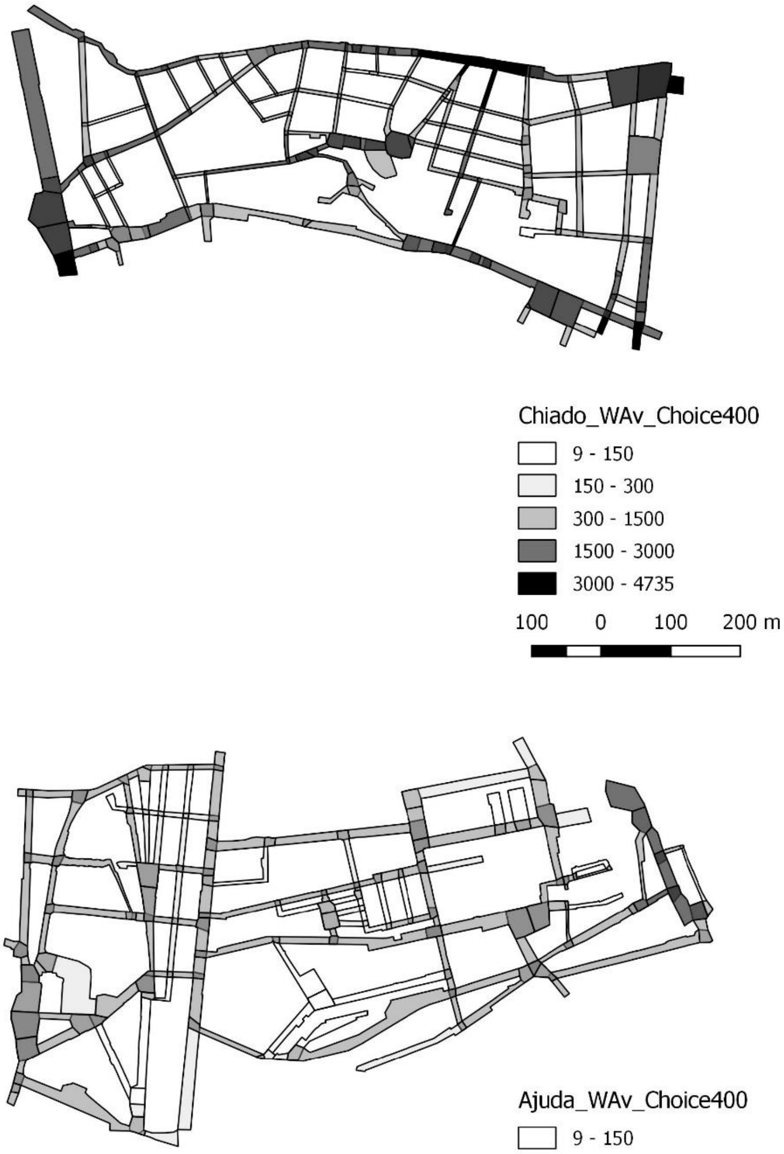


Figure E.6 : Lisbon WAv of Choice for 400m per street segment per STV.

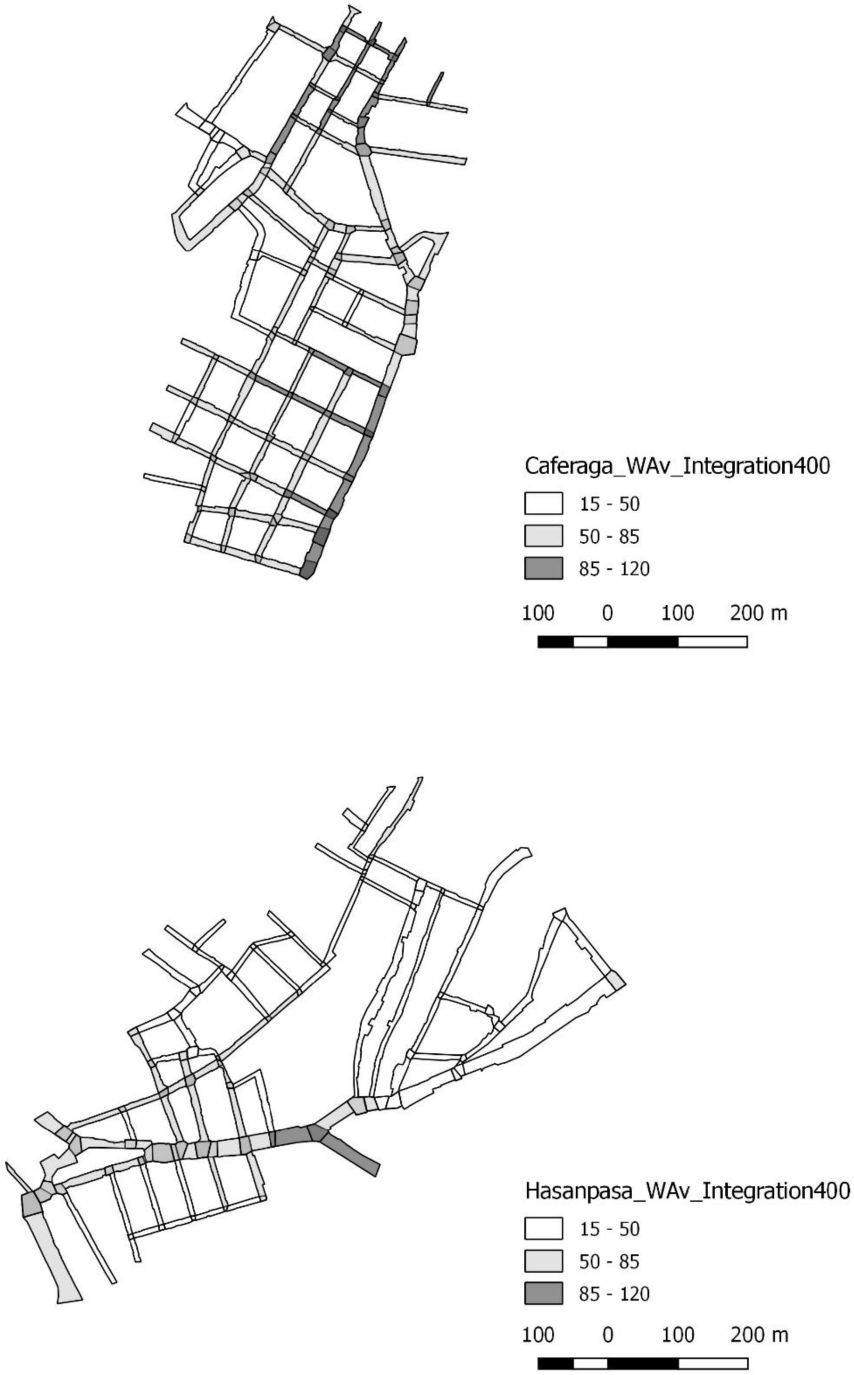


Figure E.7 : Istanbul WAv of Integration for 400m per street segment per STV.

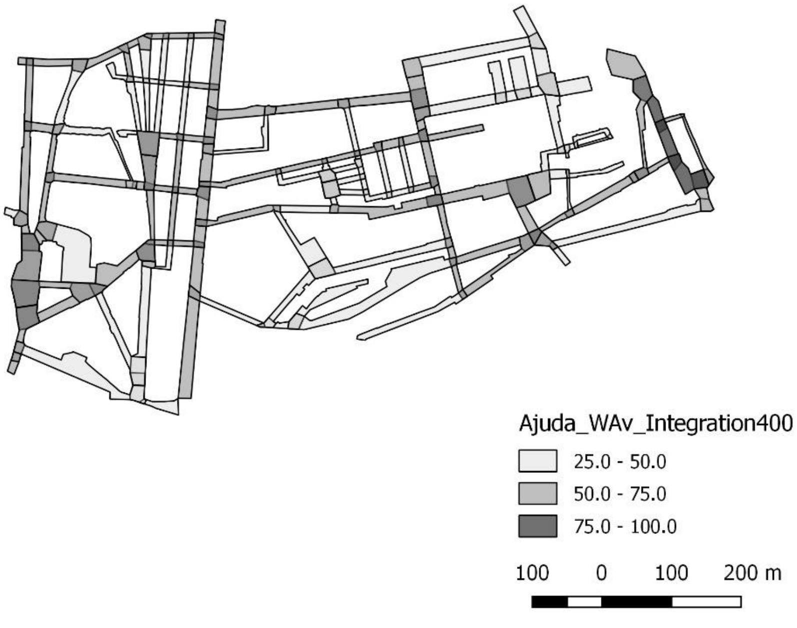
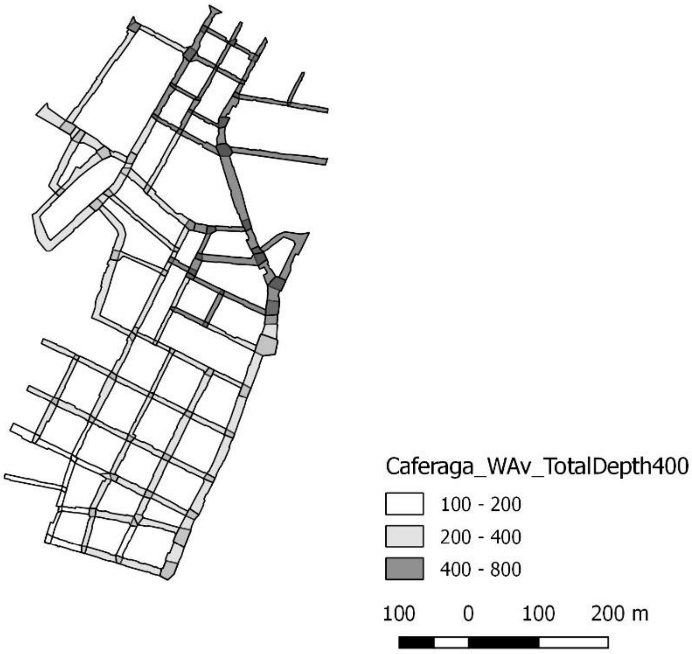


Figure E.8 : Lisbon WAv of Integration values for 400m per street segment per STV.



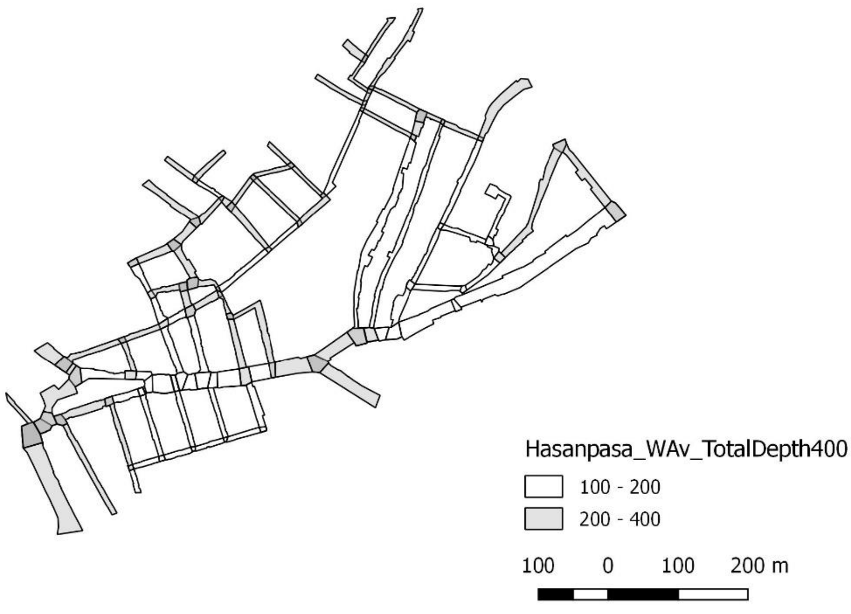


Figure E.9 : Istanbul WAv of Total Depth values for 400m per street segment per STV.

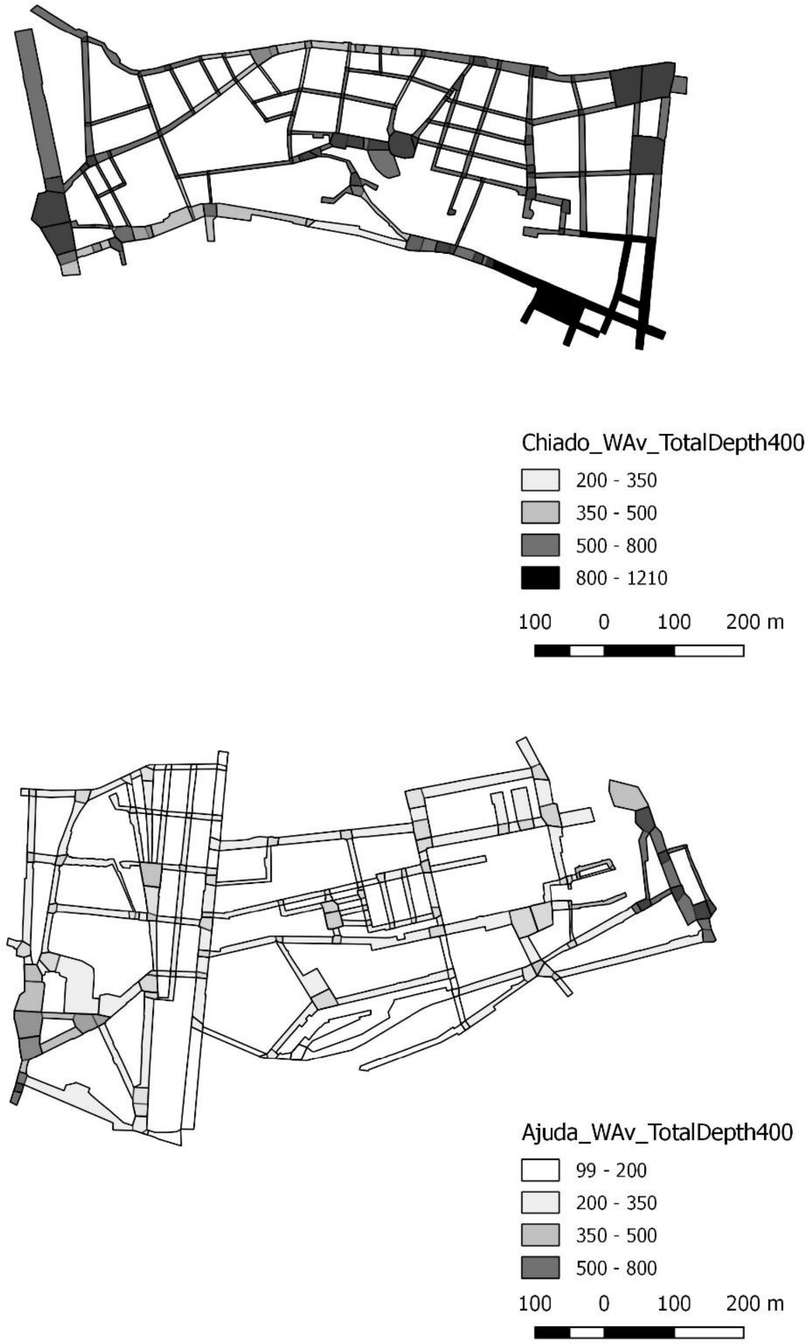
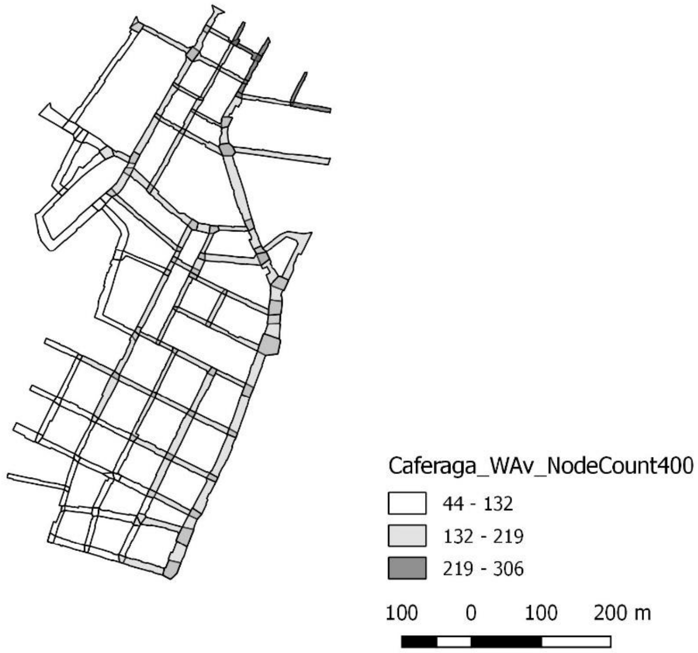


Figure E.10 : Lisbon WAv of Total Depth values for 400m per street segment per STV.



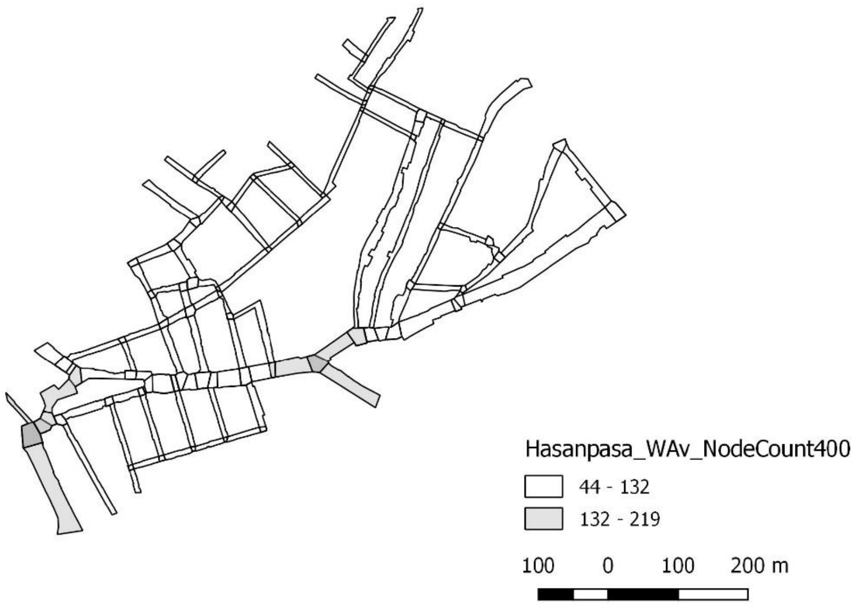


Figure E.11 : Istanbul WAv of Node Count values for 400m per street segment per STV.

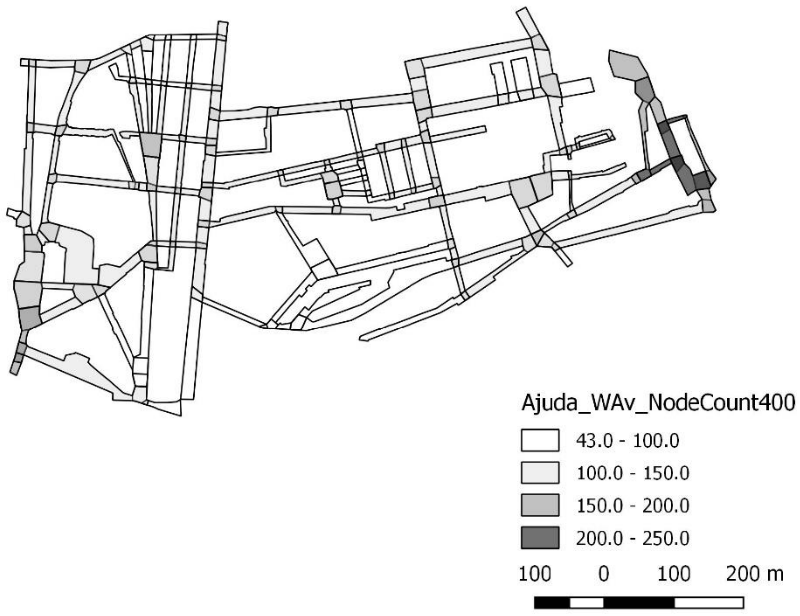


Figure E.12 : Lisbon WAv of Node Count values for 400m per street segment per STV

APPENDIX F

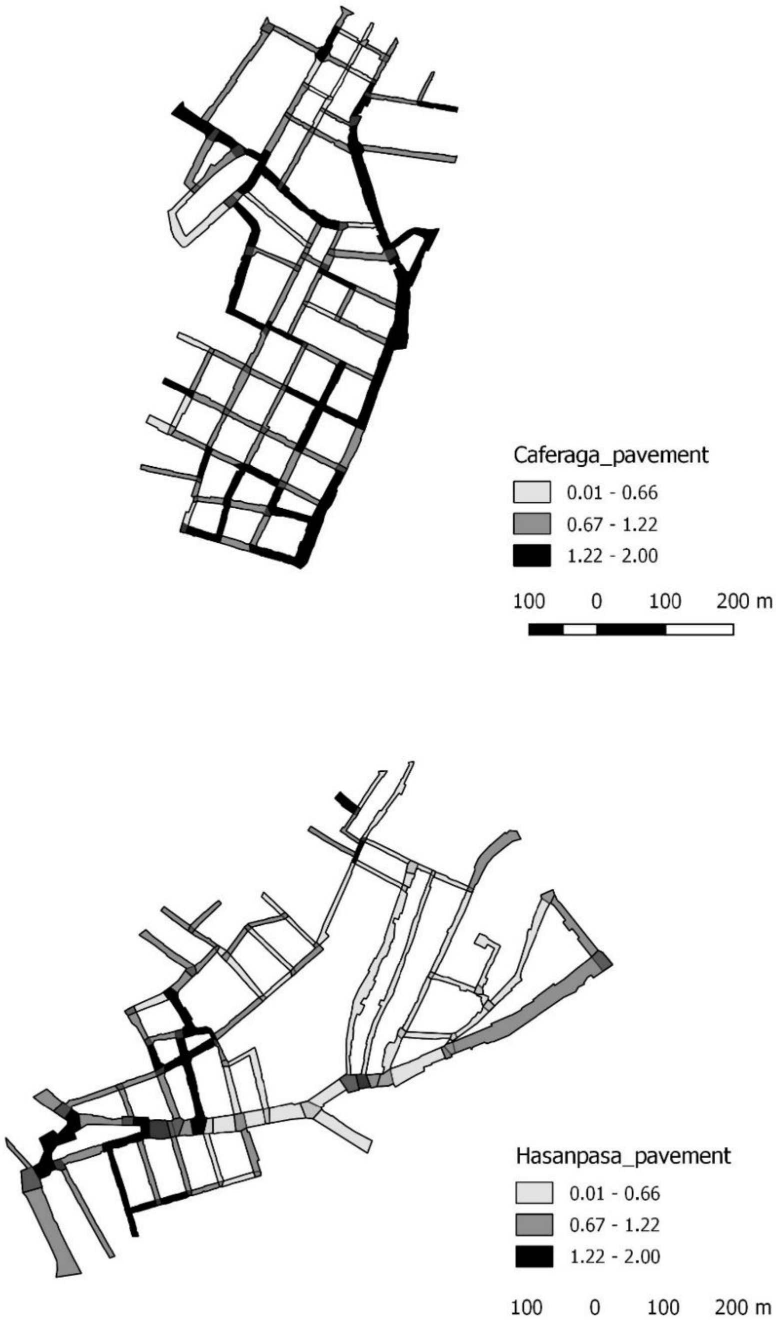
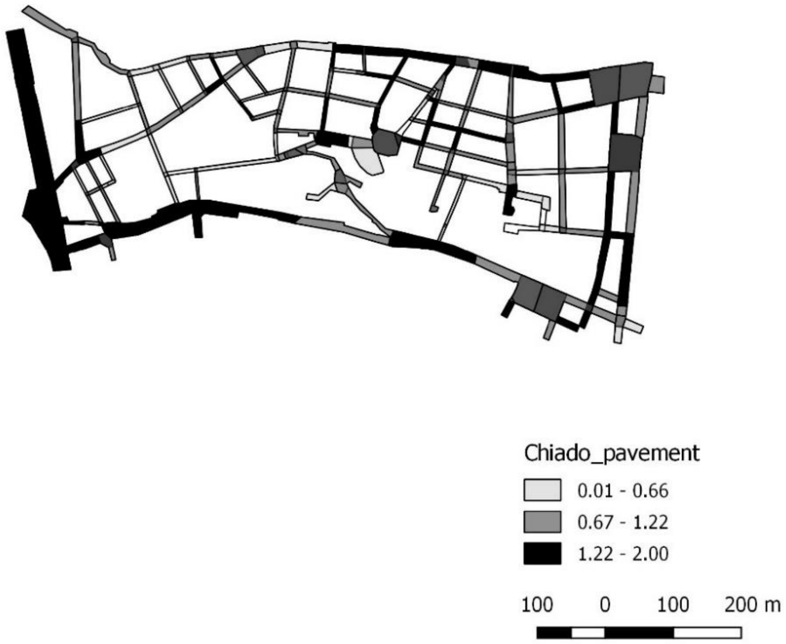


Figure F.1 : Istanbul ANSS where a sidewalk is identified.



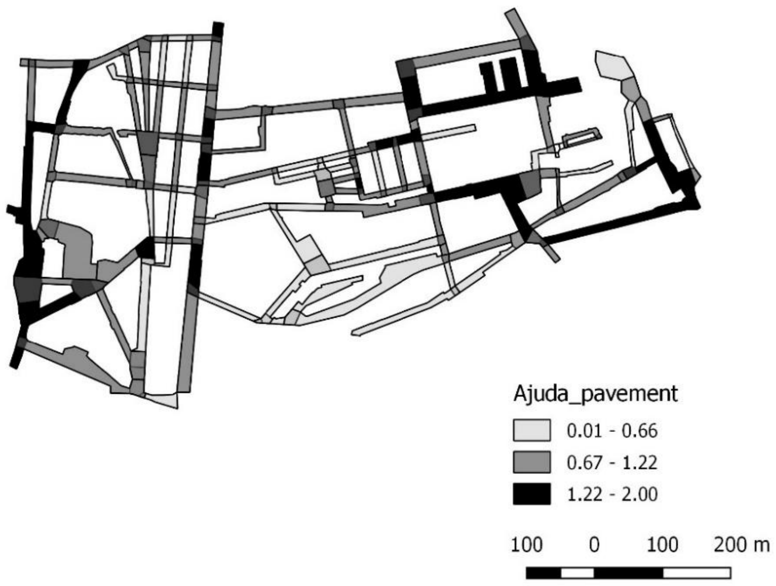


Figure F.2 : Lisbon ANSS where a sidewalk is identified.

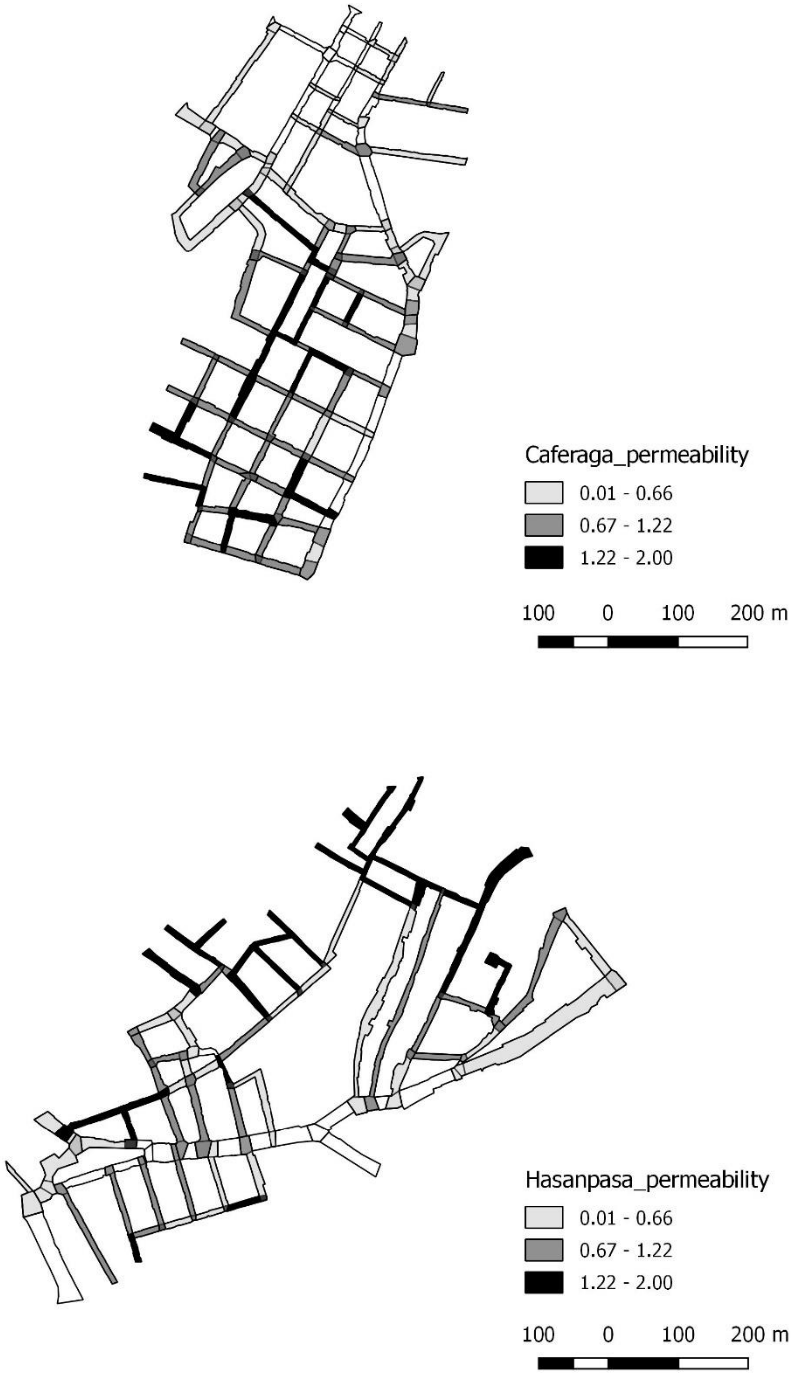
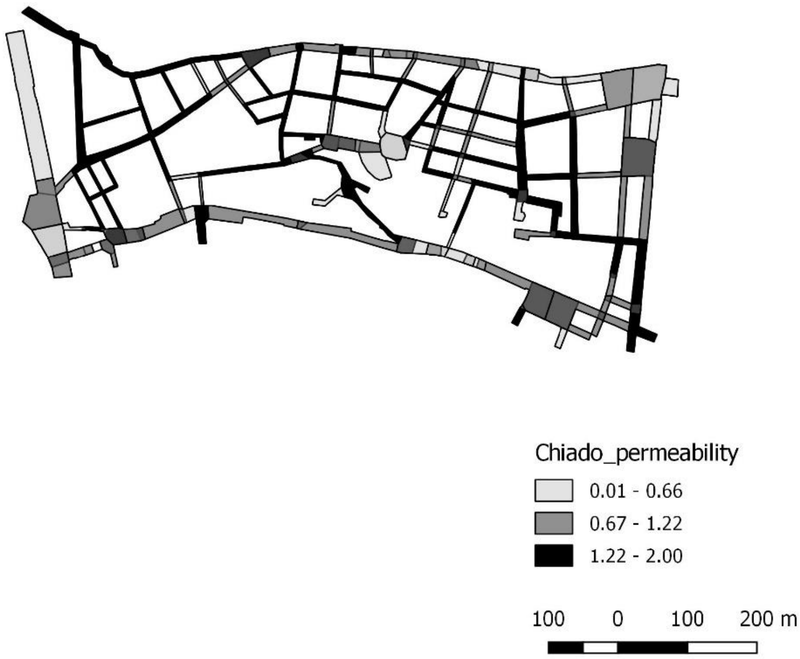


Figure F.3 : Istanbul ANSS where doors or windows are identified.



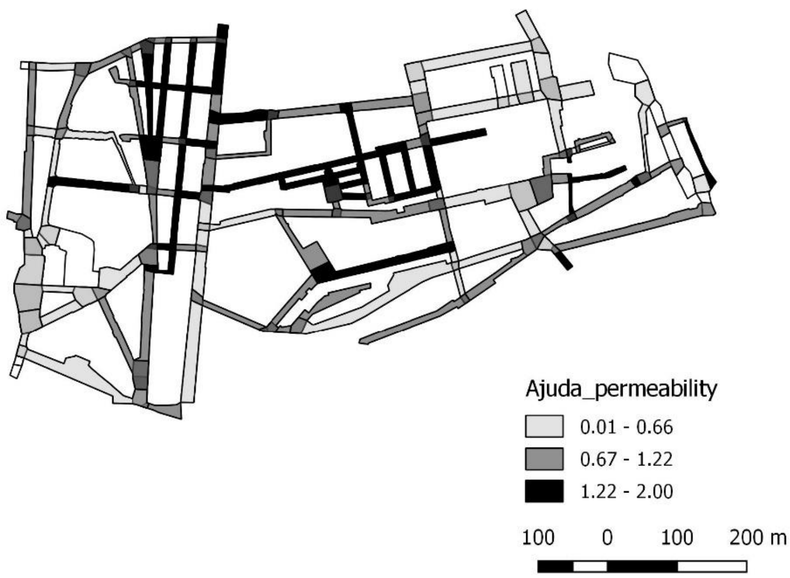


Figure F.4 : Lisbon ANSS where doors or windows are identified.

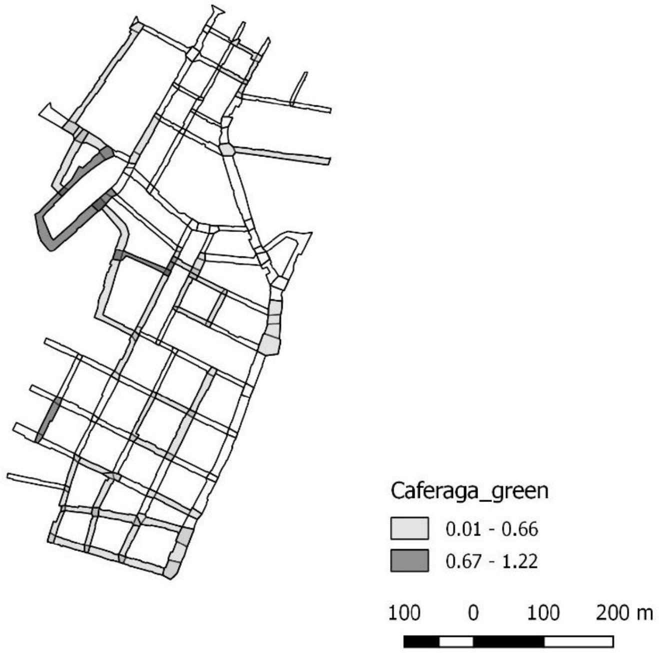


Figure F.5 : Istanbul ANSS where “trees”, “landscape”, ”parks” or “environment” tags are identified.

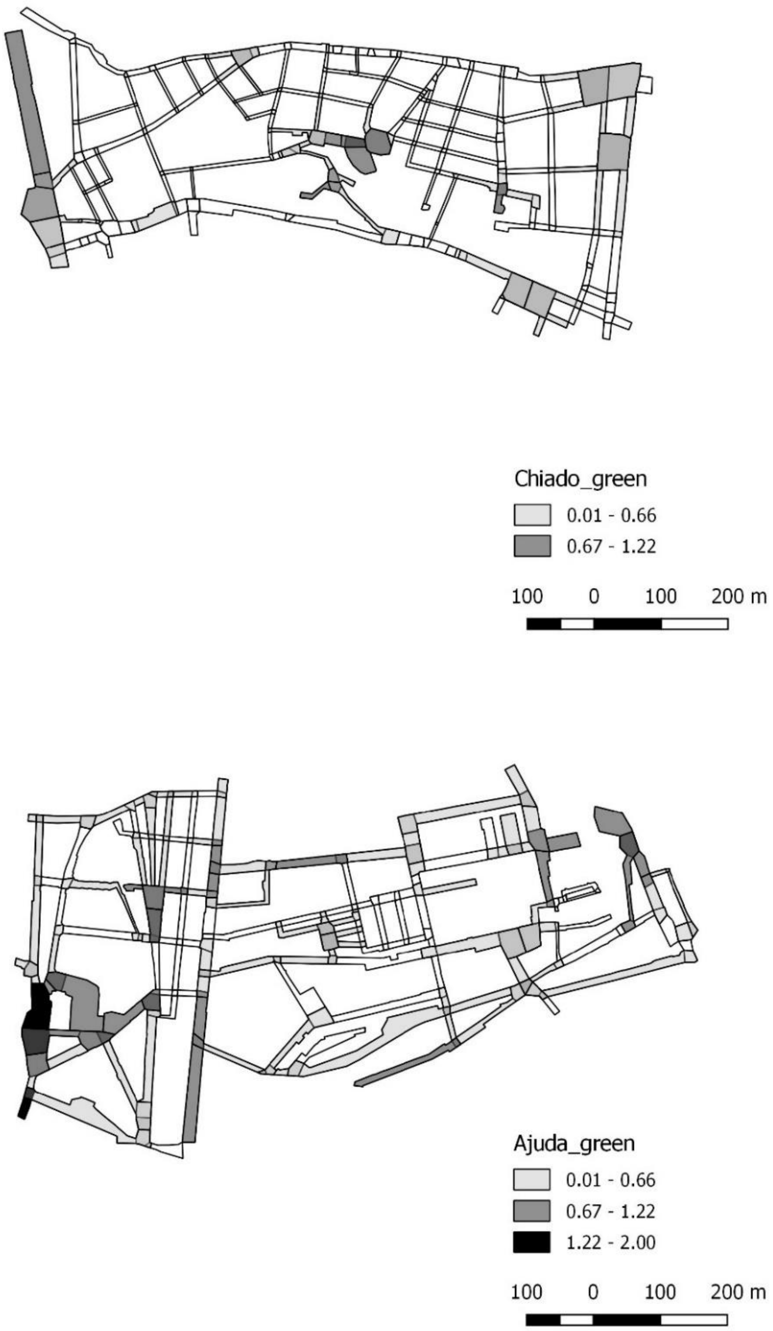


Figure F.6 : Lisbon ANSS where “trees”, “landscape”, ”parks” or “environment” tags are identified.

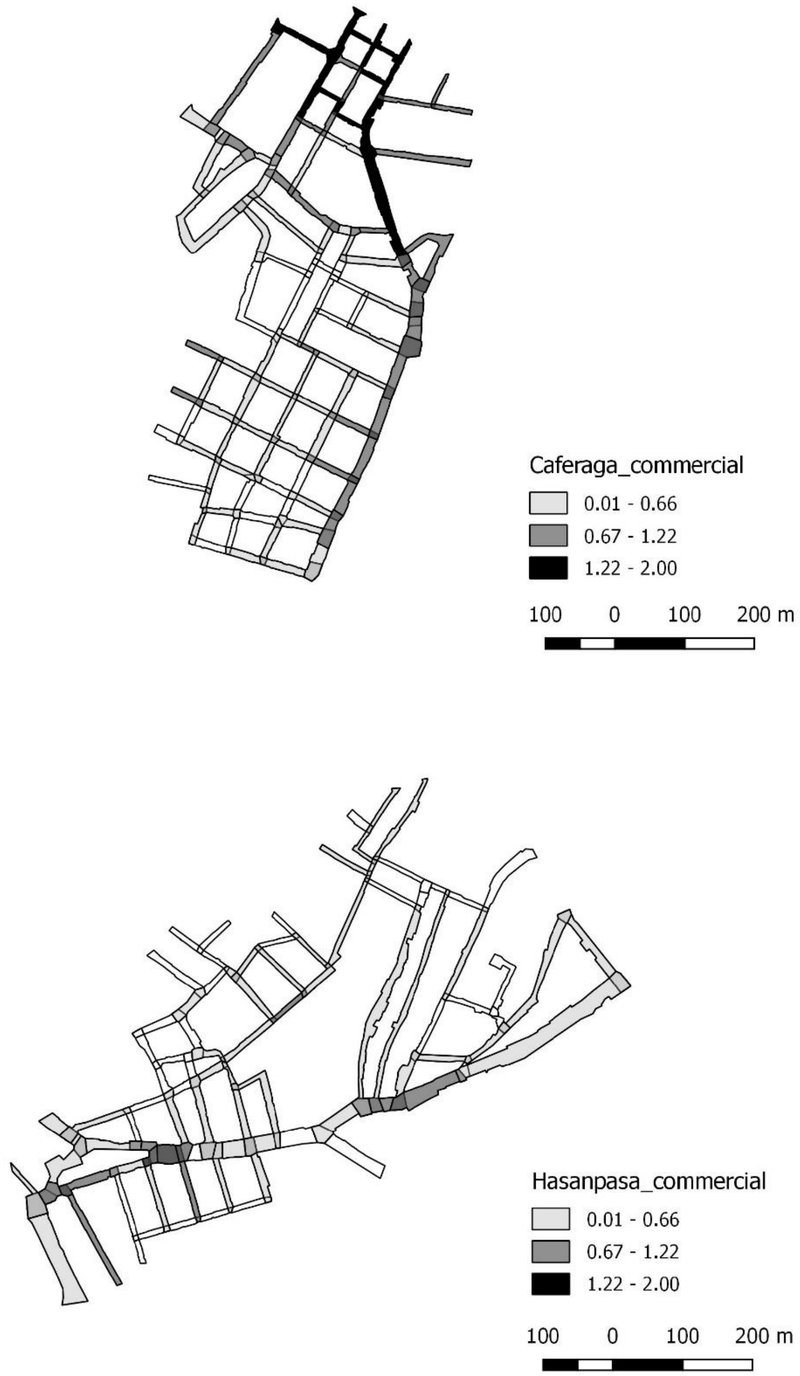
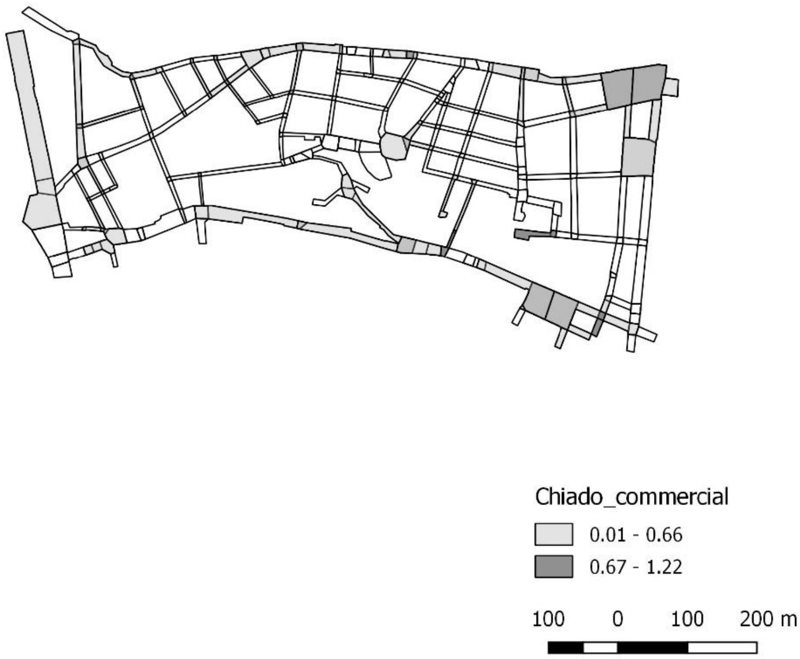


Figure F.7 : Istanbul ANSS where “commercial”, “shopping” or “business” tags are identified.



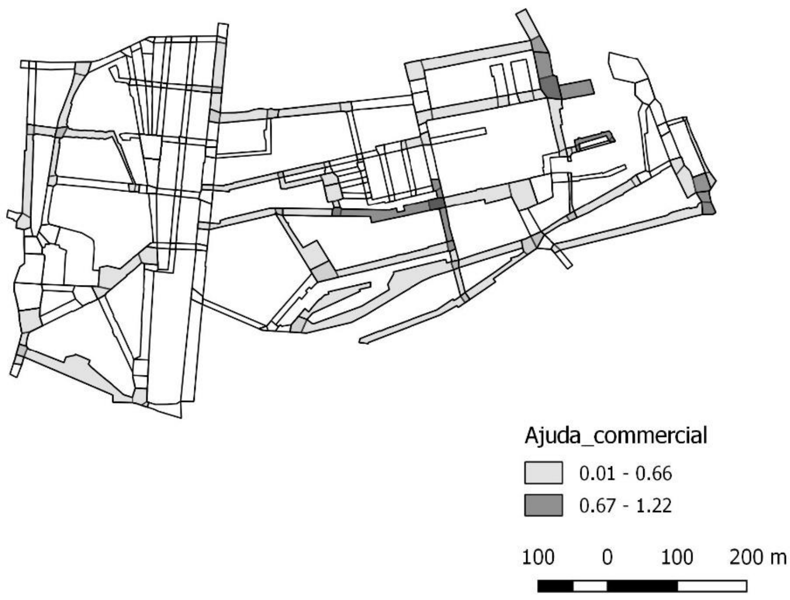


Figure F.8 : Lisbon ANSS where “commercial”, “shopping” or “business” tags are identified.

Figure F.9 : Istanbul ANSS where “benches”, “chairs” or “street furniture” tags are identified.

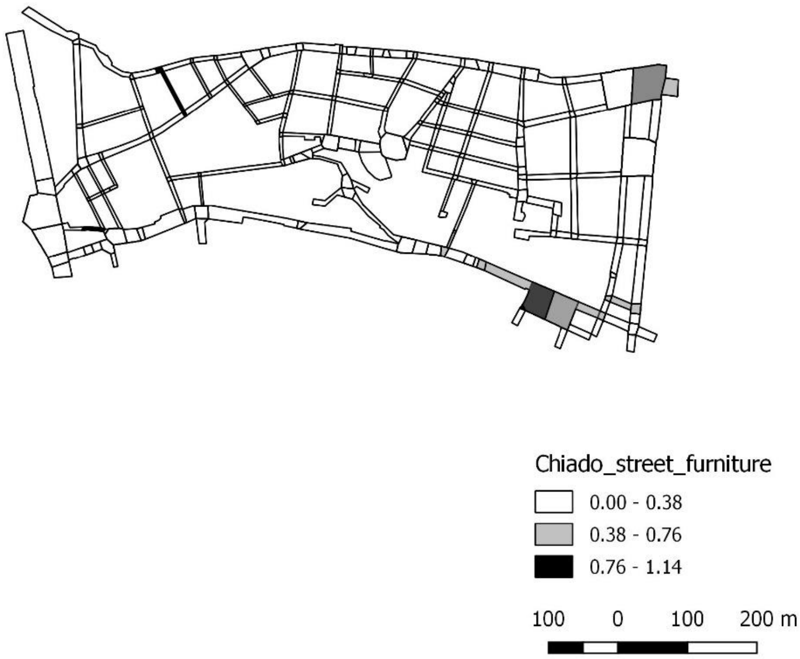
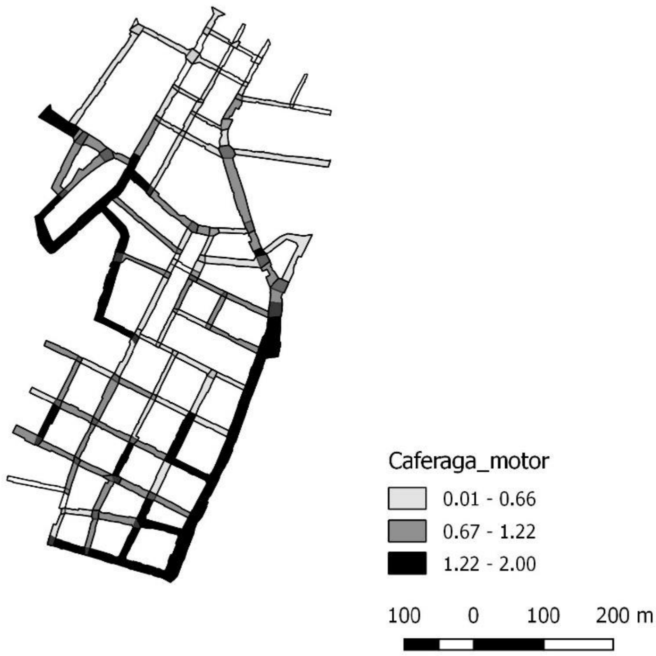


Figure F.10 : Lisbon ANSS where “benches”, “chairs” or “street furniture” tags are identified.



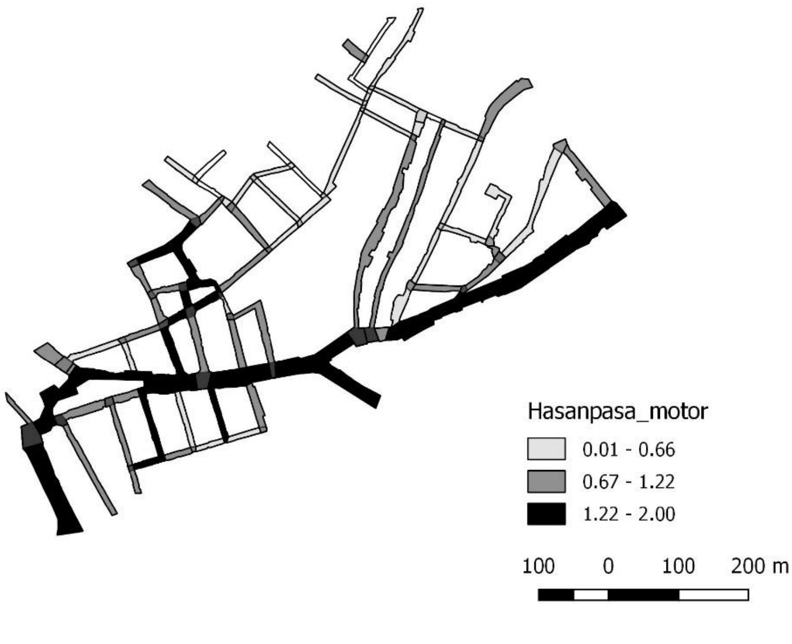
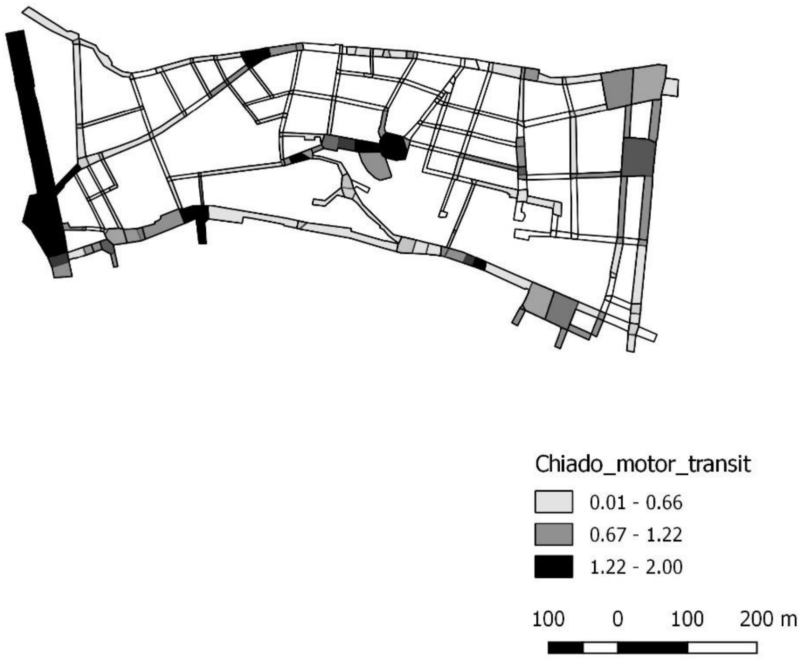


Figure F.11 : Istanbul ANSS where “cars”, “vehicles” or “traffic” tags are identified.



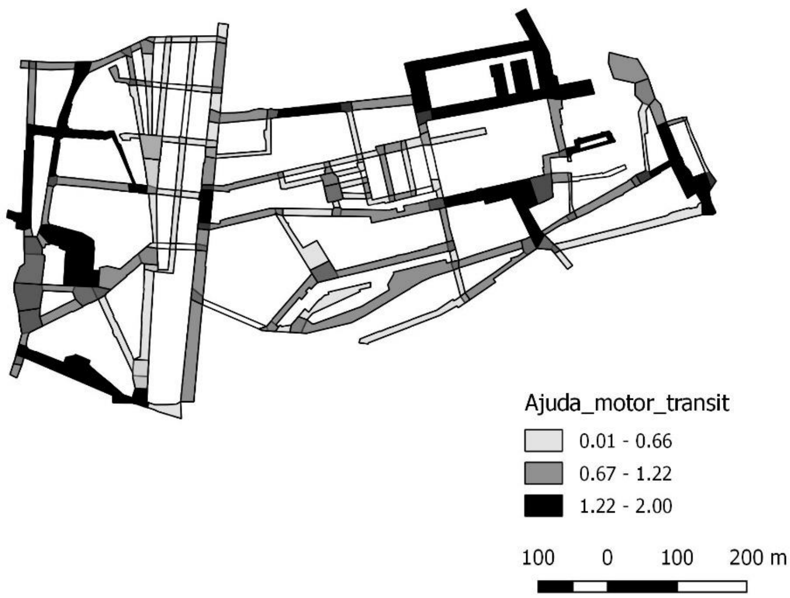
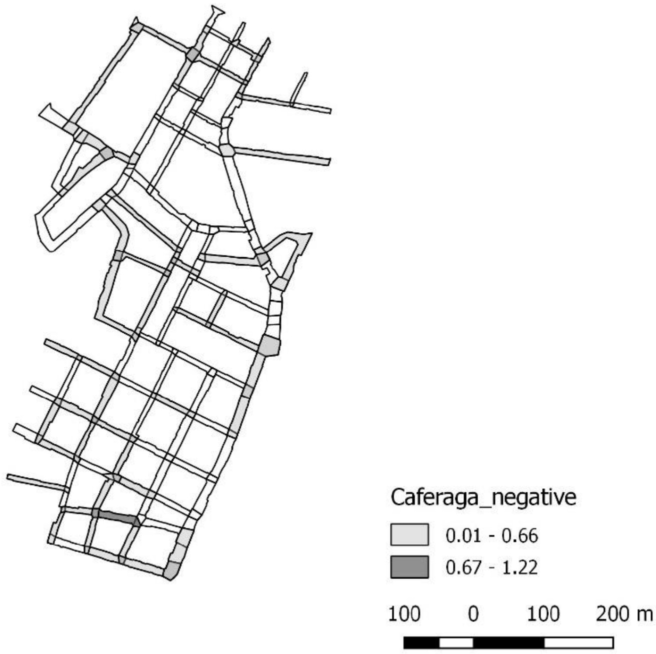


Figure F.12 : Lisbon ANSS where “cars”, “vehicles” or “traffic” tags are identified.



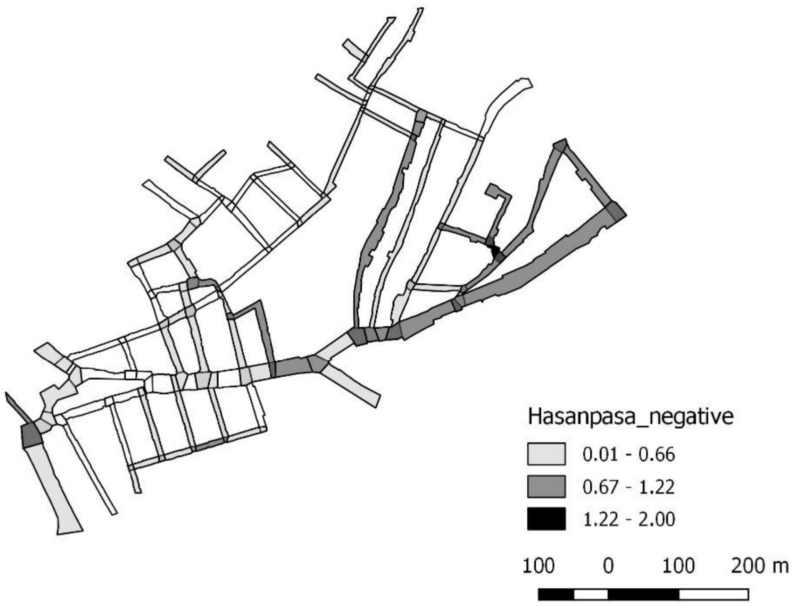
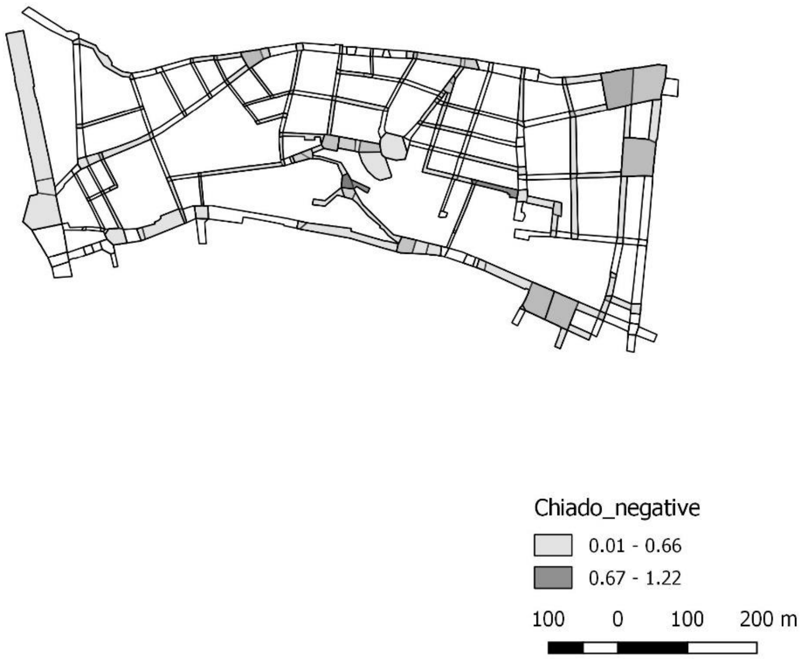


Figure F.13 : Istanbul ANSS where “abandoned”, “calamity” or “demolished” tags are identified.



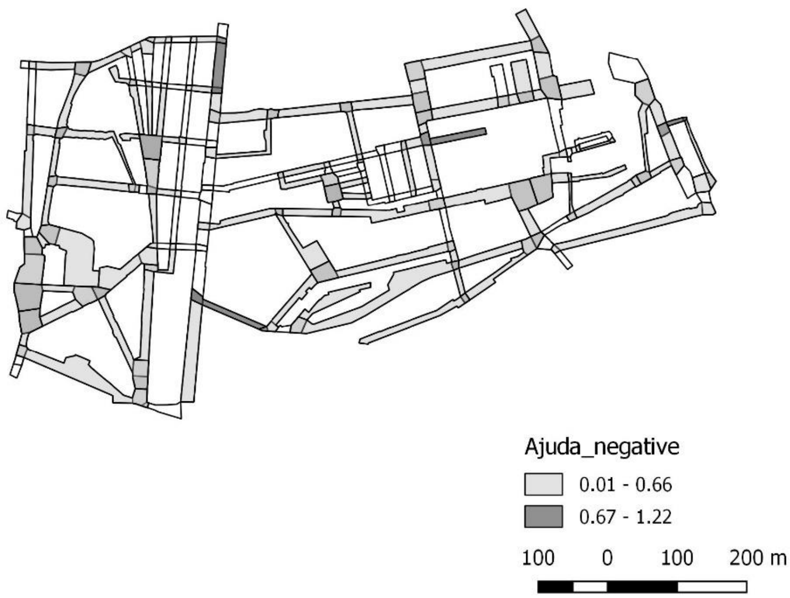


Figure F.14 : Lisbon ANSS where “abandoned”, “calamity” or “demolished” tags are identified.

APPENDIX G

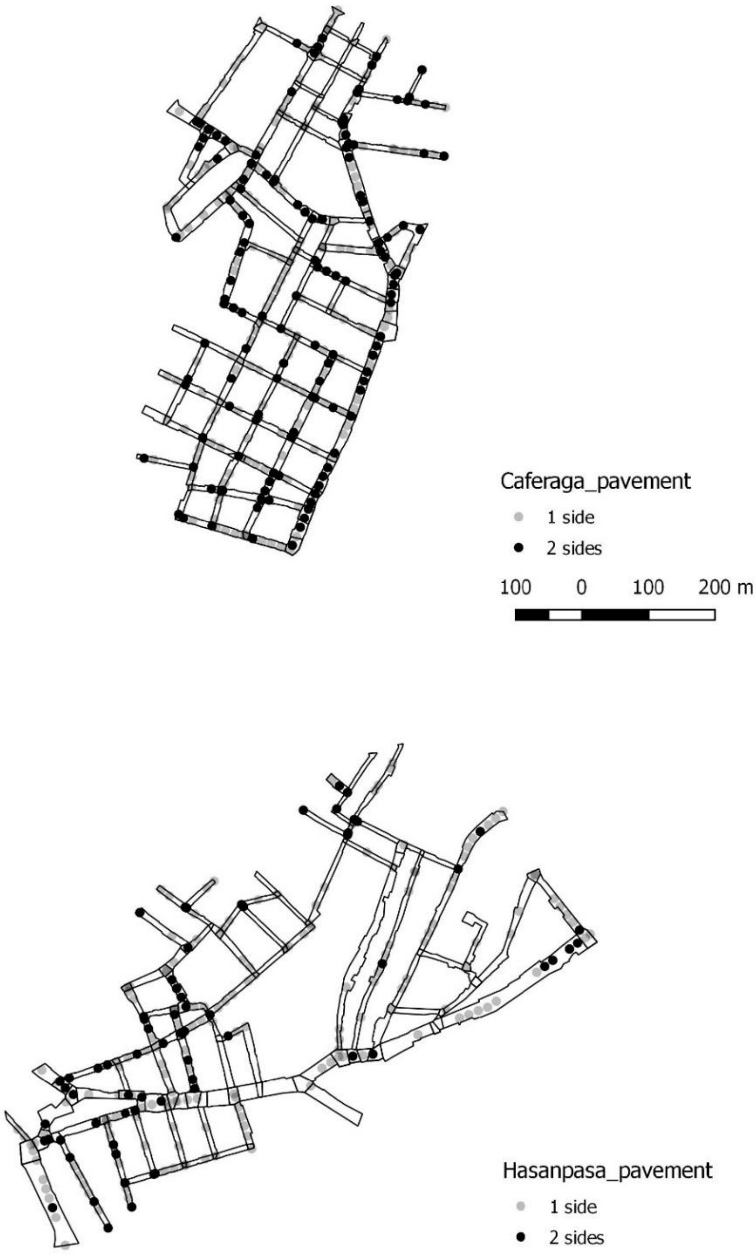
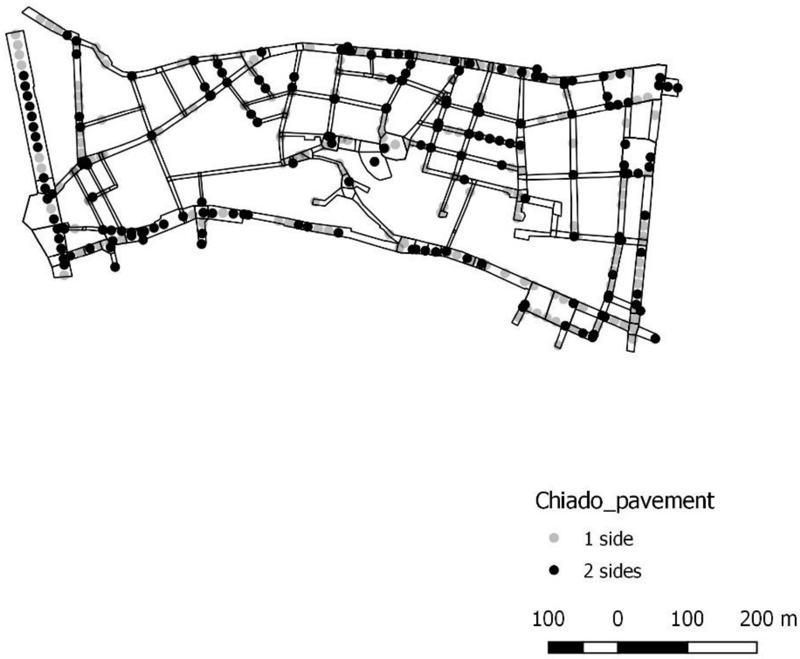


Figure G.1 : Istanbul NSS where a sidewalk is identified.



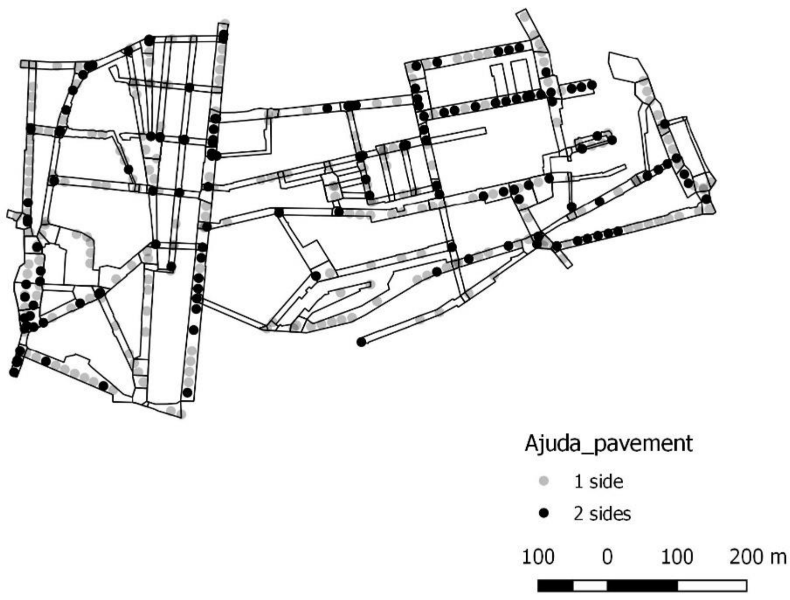
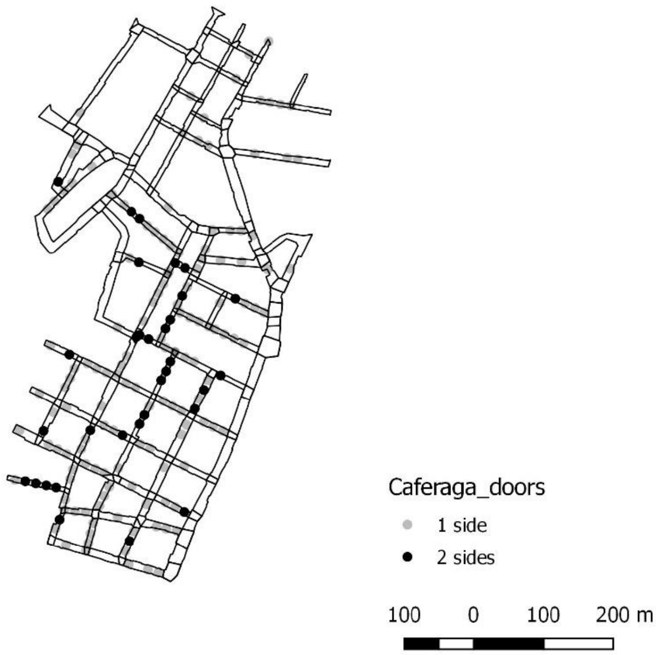


Figure G.2 : Lisbon NSS where a sidewalk is identified.



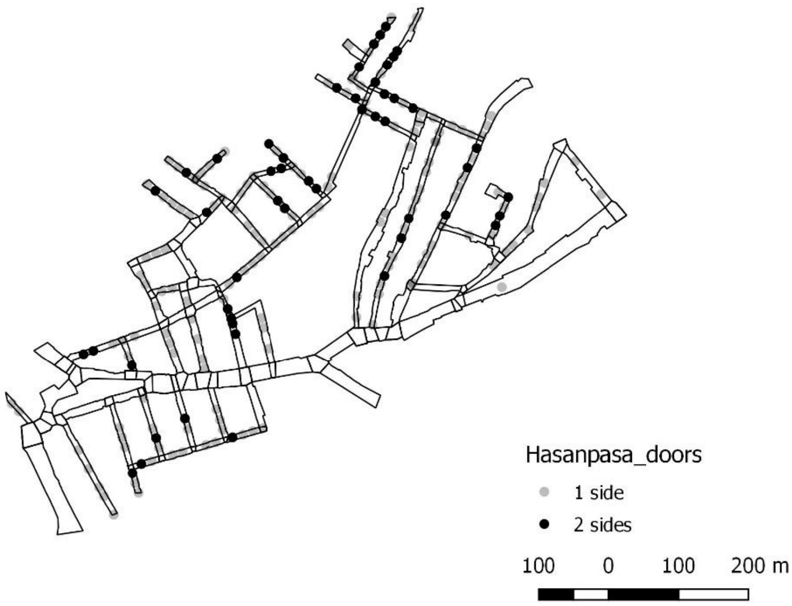
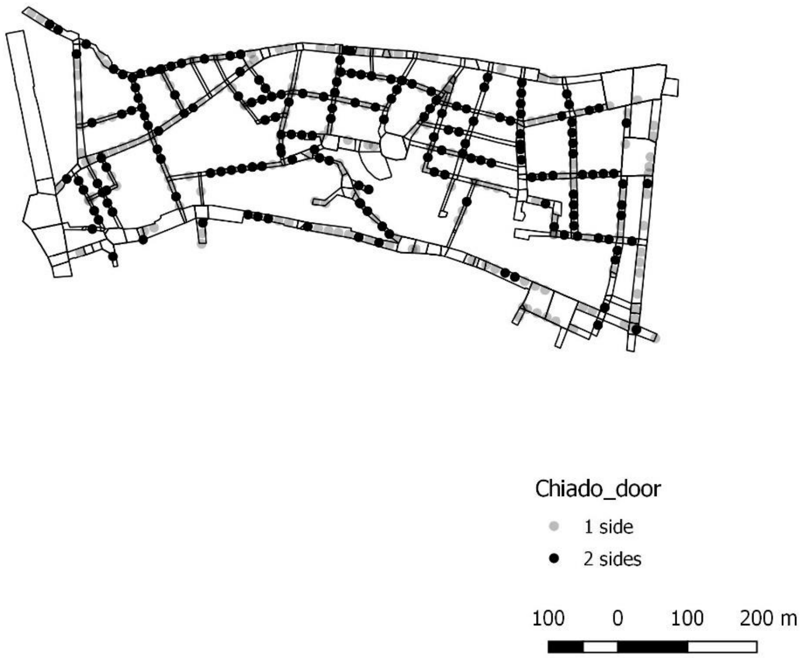


Figure G.3 : Istanbul NSS where doors are identified.



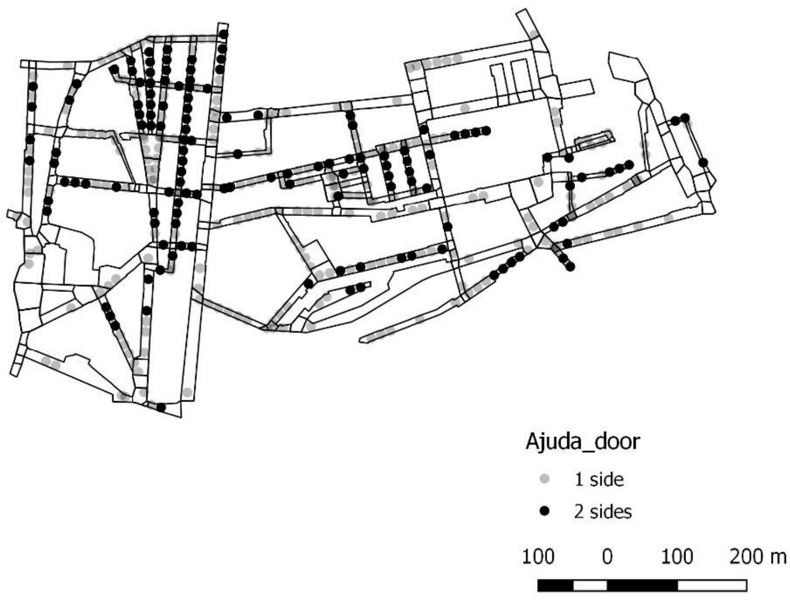
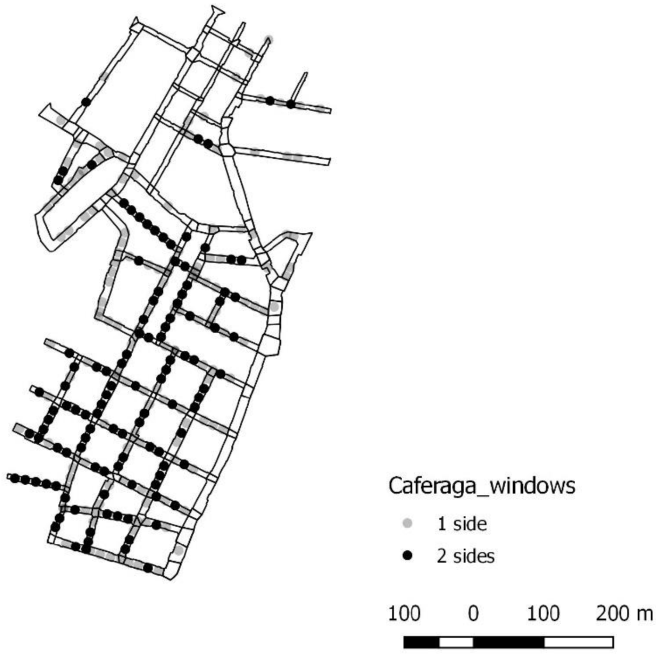


Figure G.4 : Lisbon NSS where doors are identified.



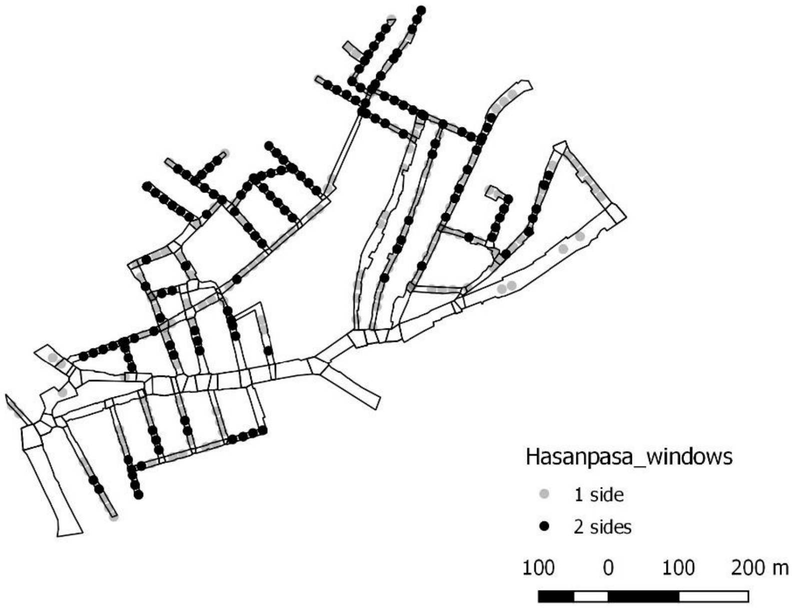
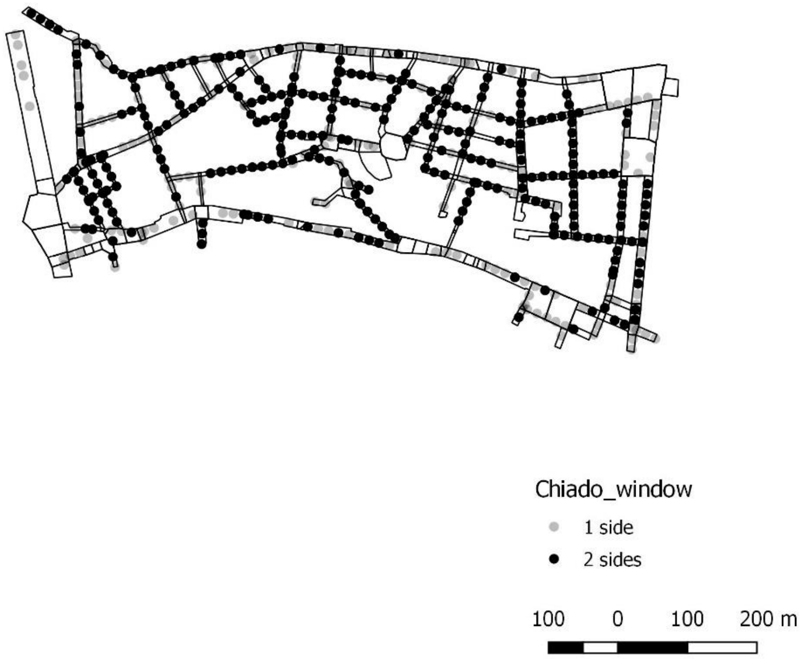


Figure G.5 : Istanbul NSS where windows are identified.



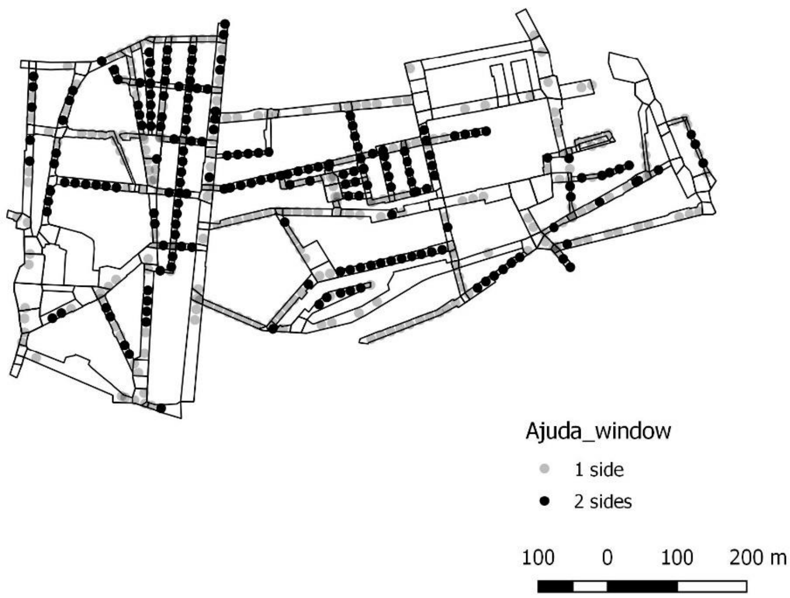


Figure G.6 : Lisbon NSS where windows are identified.

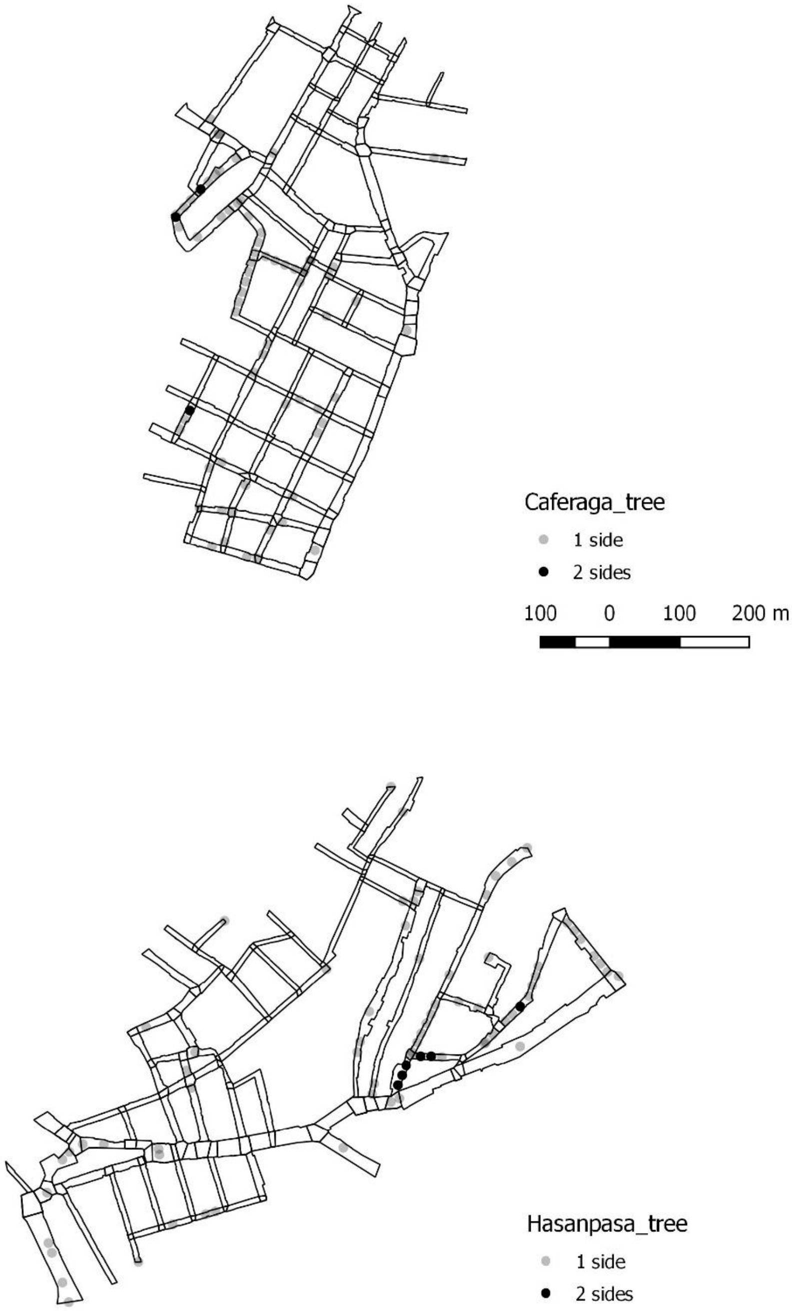
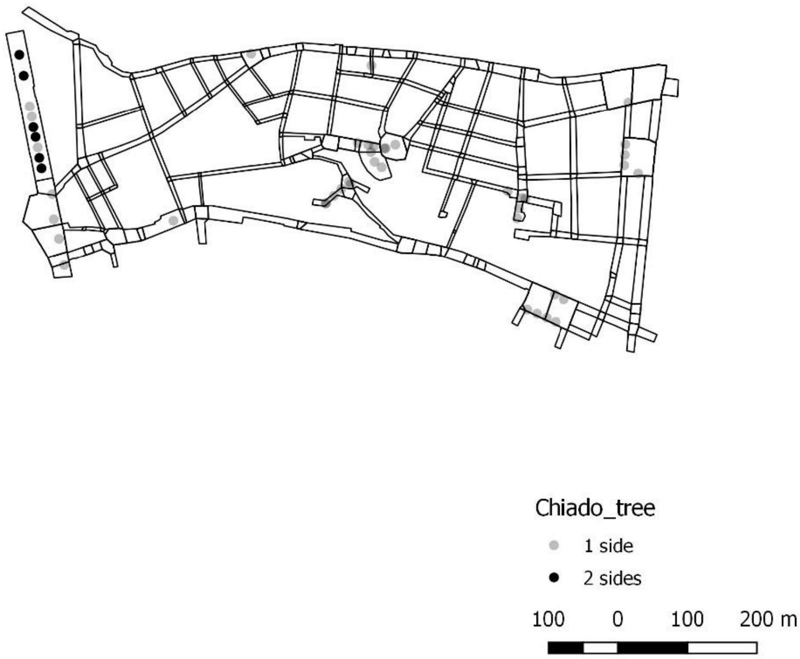


Figure G.7 : Istanbul NSS where trees are identified.



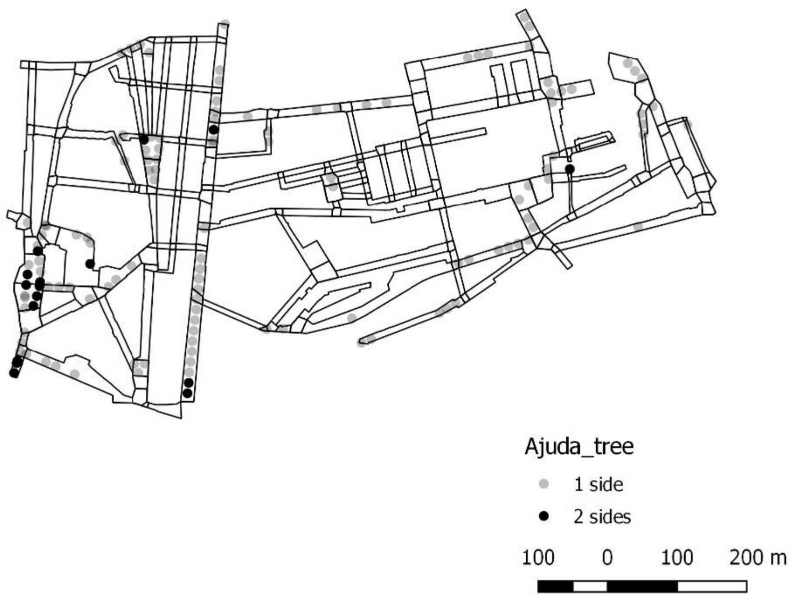


Figure G.8 : Lisbon NSS where trees are identified.

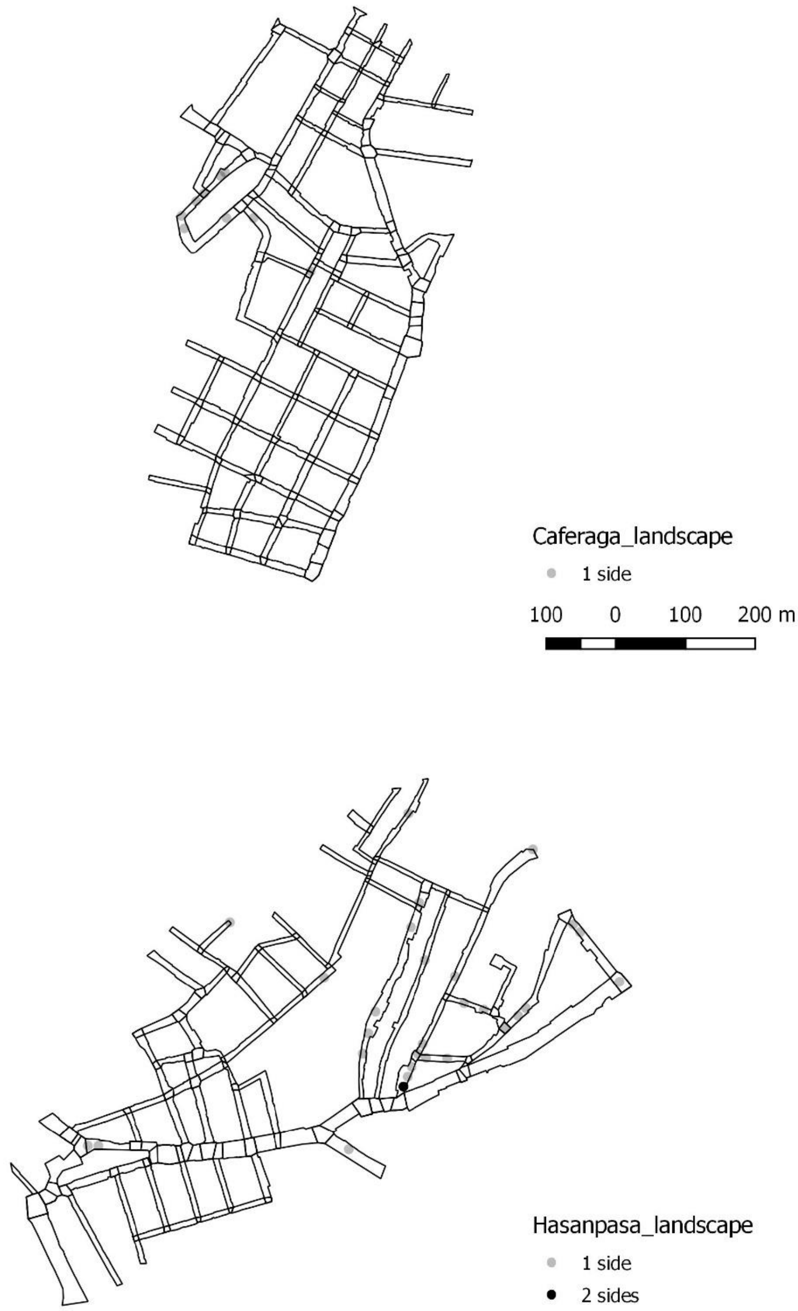
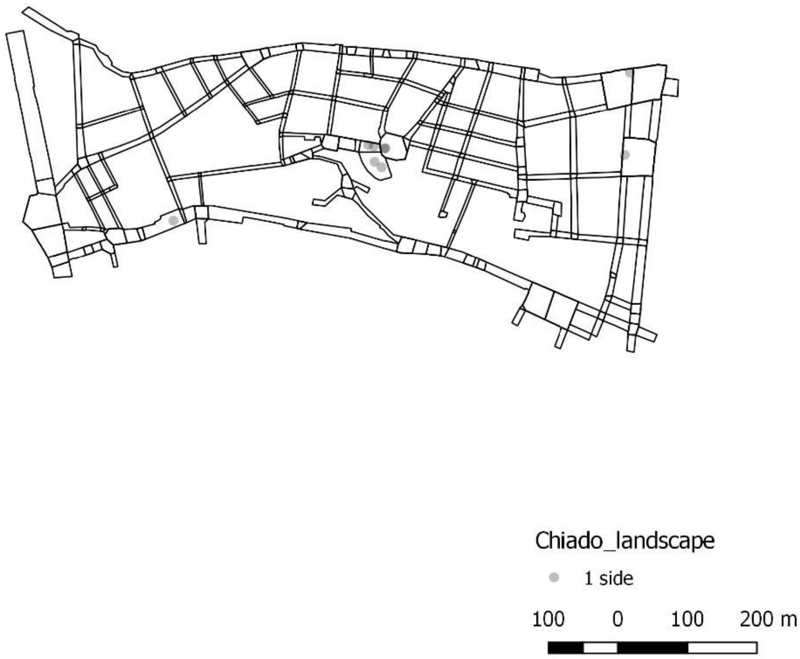


Figure G.9 : Istanbul NSS where landscape is identified.



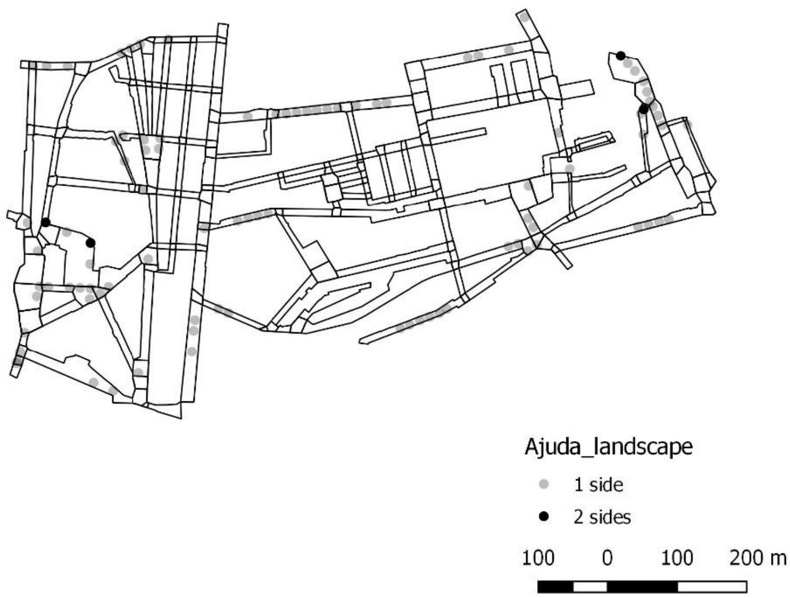
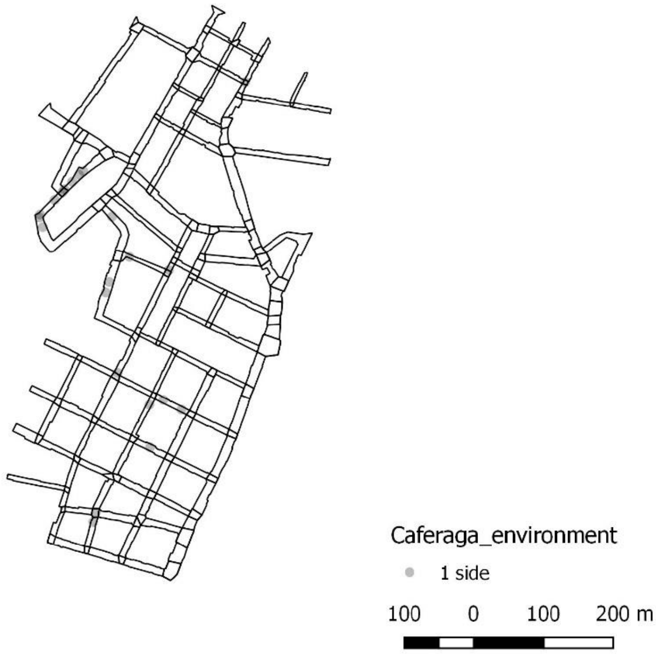


Figure G.10 : Lisbon NSS where landscape is identified.



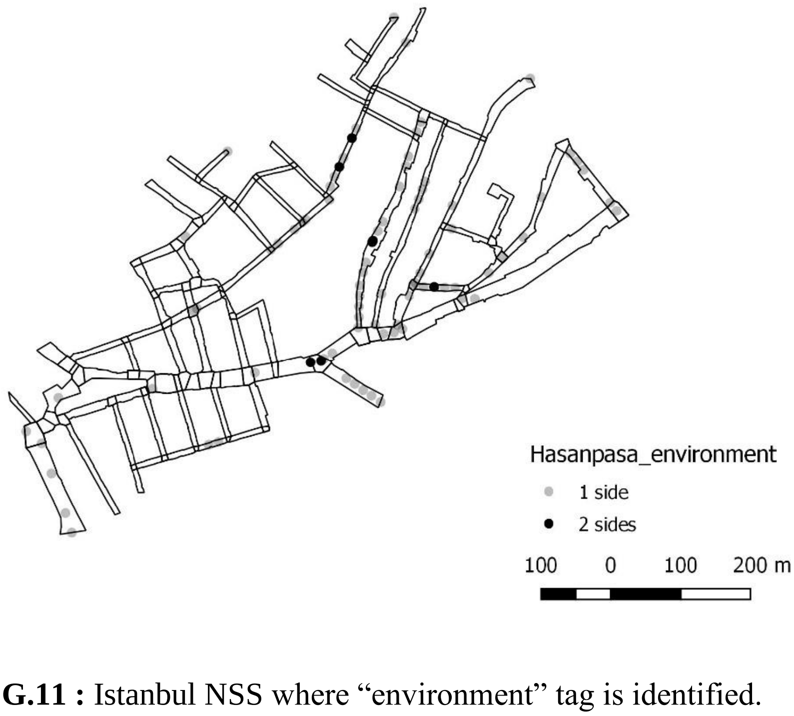
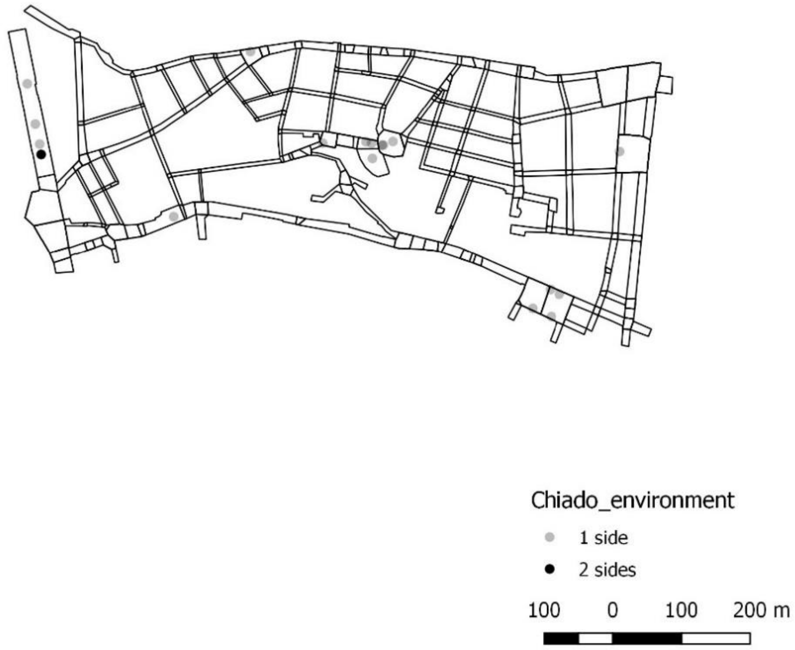


Figure G.11 : Istanbul NSS where “environment” tag is identified.



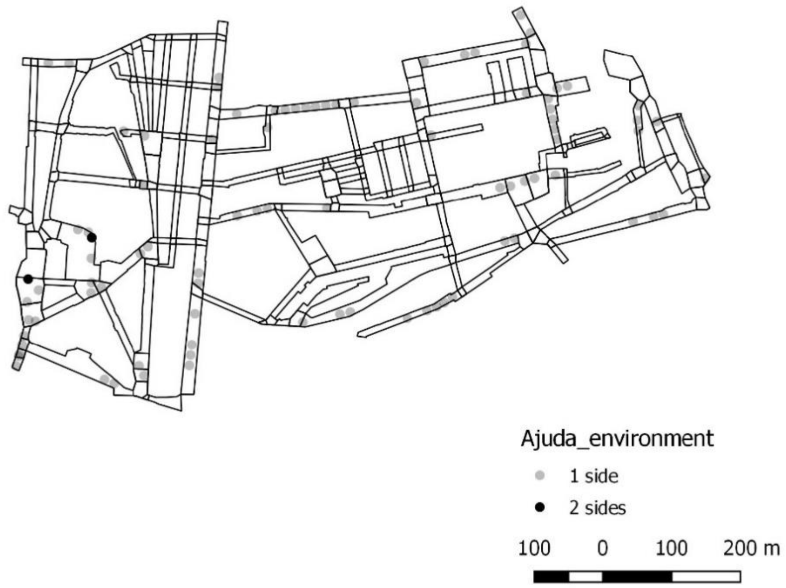
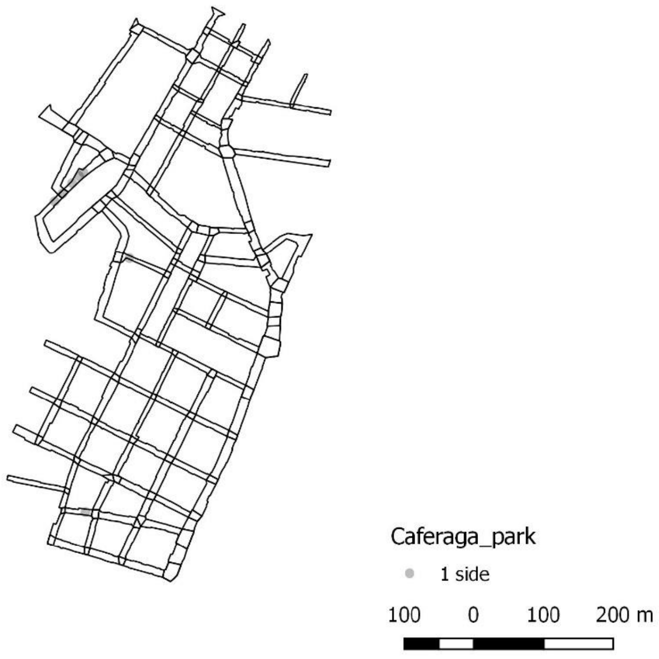


Figure G.12 : Lisbon NSS where “environment” tag is identified.



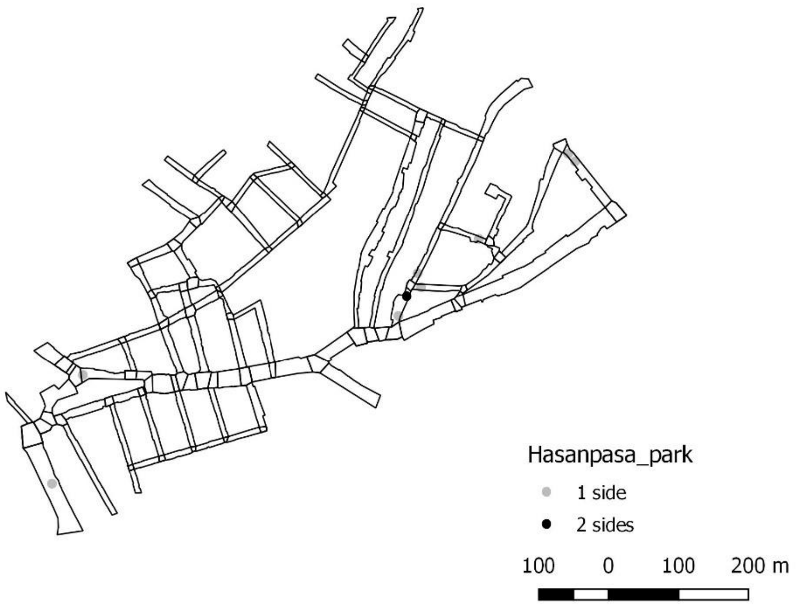
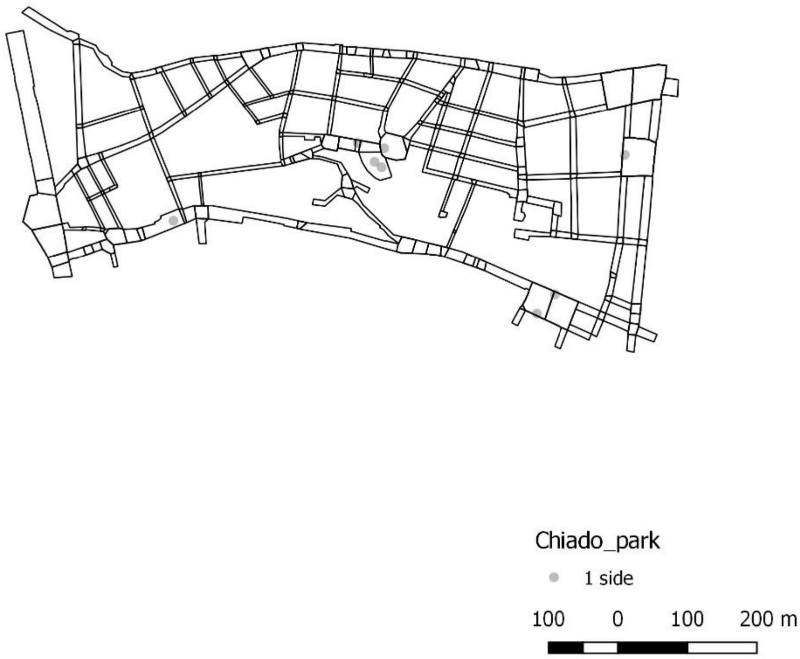


Figure G.13 : Istanbul NSS where a park is identified.



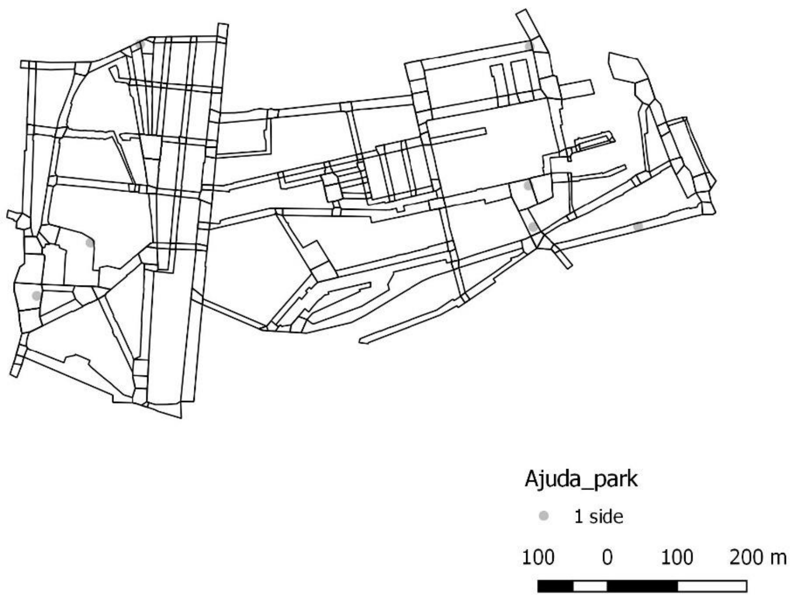
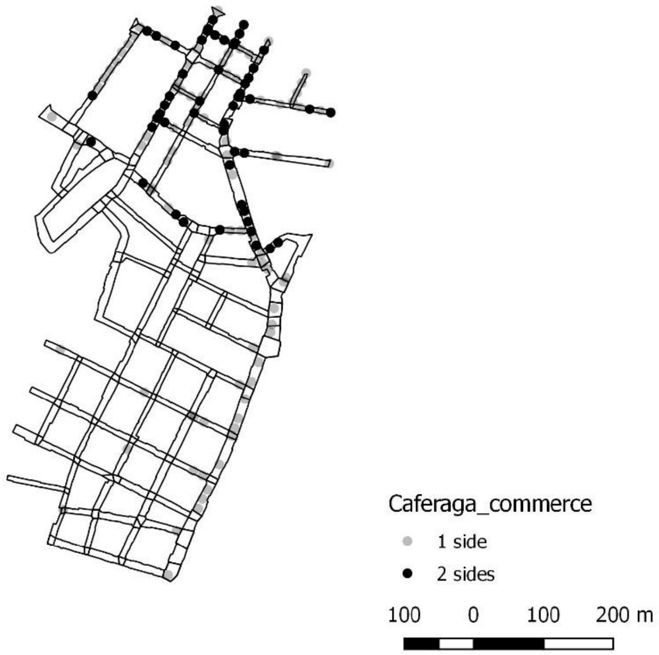


Figure G.14 : Istanbul NSS where a park is identified.



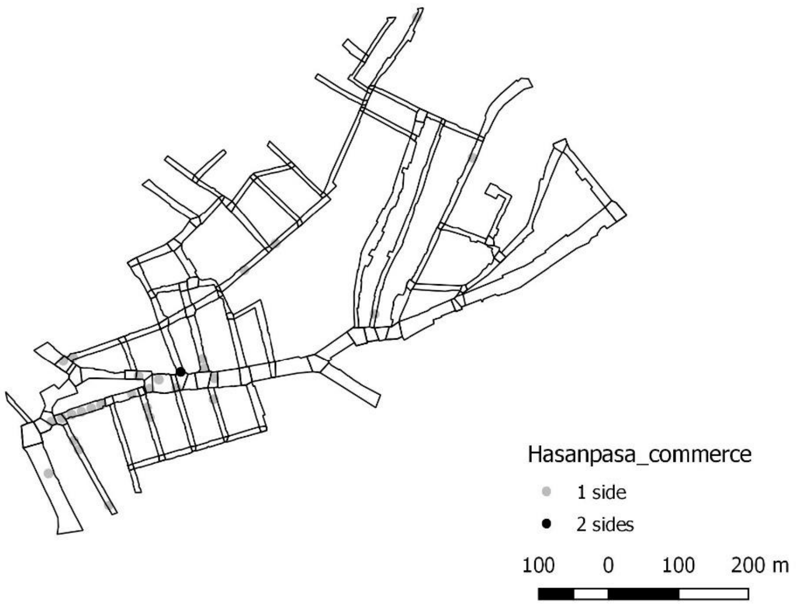
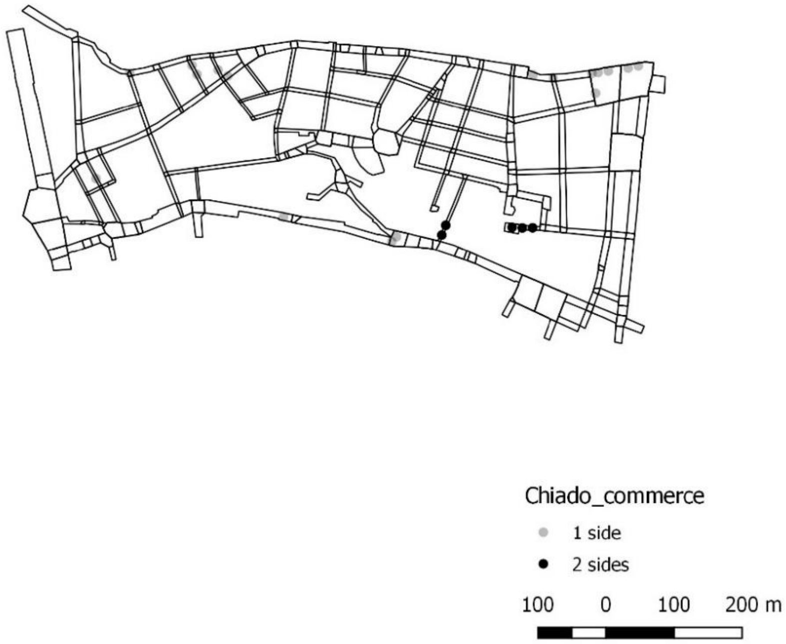


Figure G.15 : Istanbul NSS where commercial activity is identified.



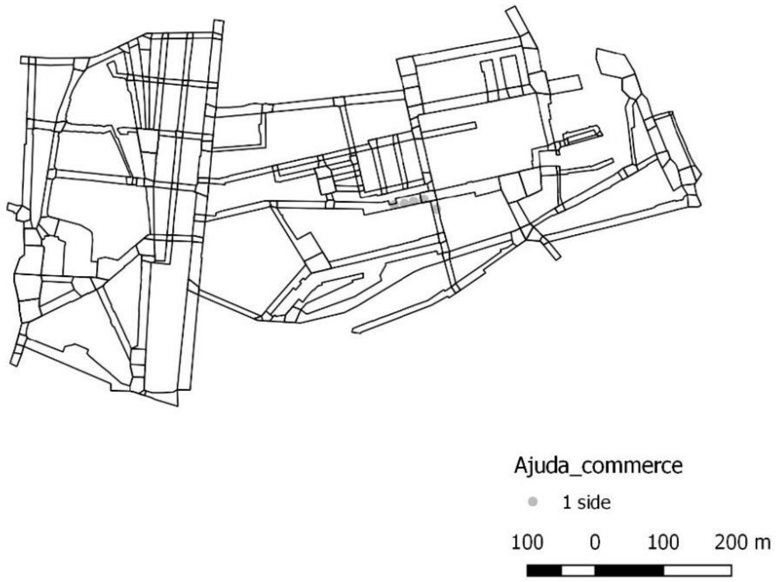
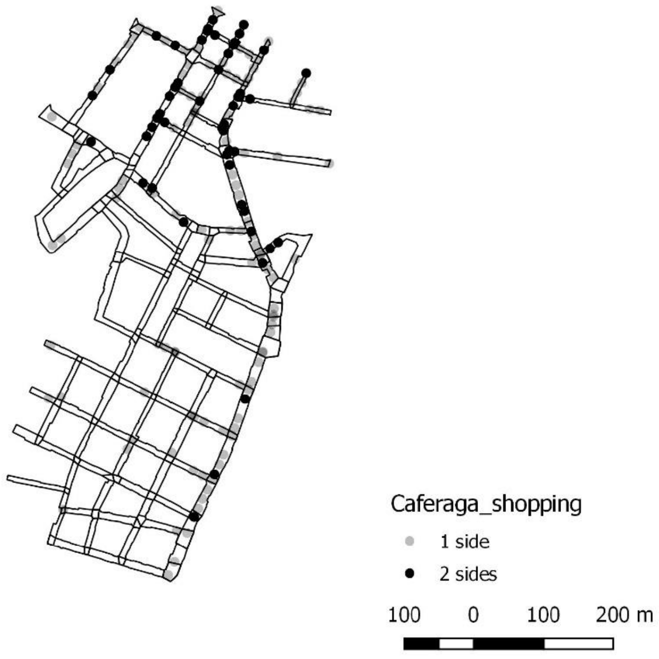


Figure G.16 : Lisbon NSS where commercial activity is identified.



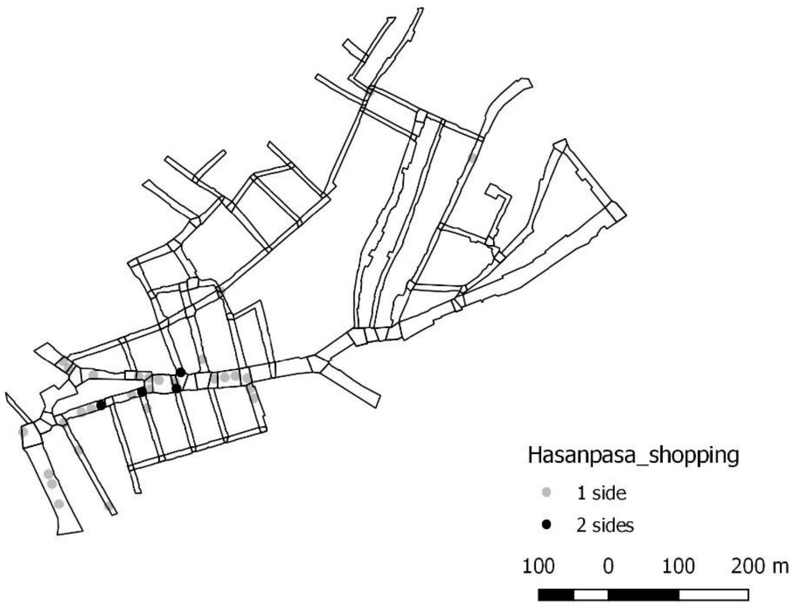
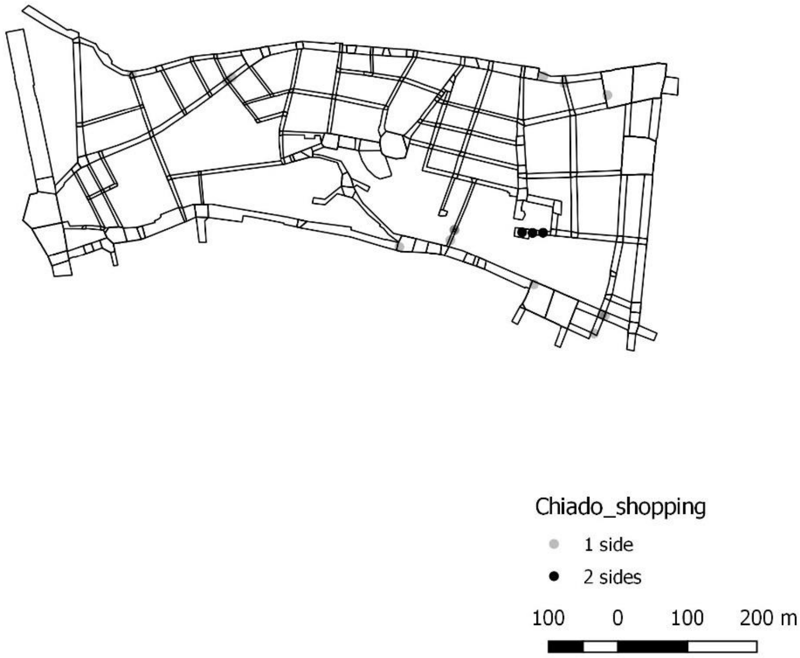


Figure G.17 : Istanbul NSS where shopping activity is identified.



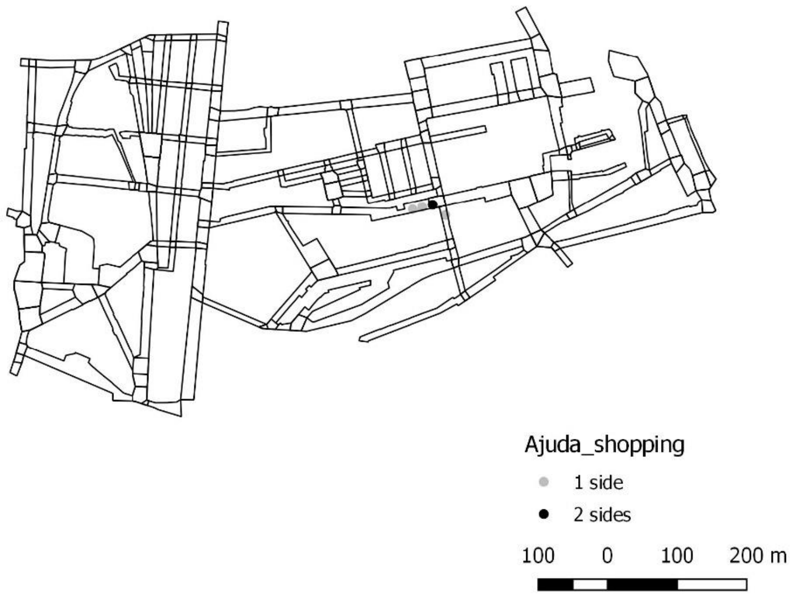
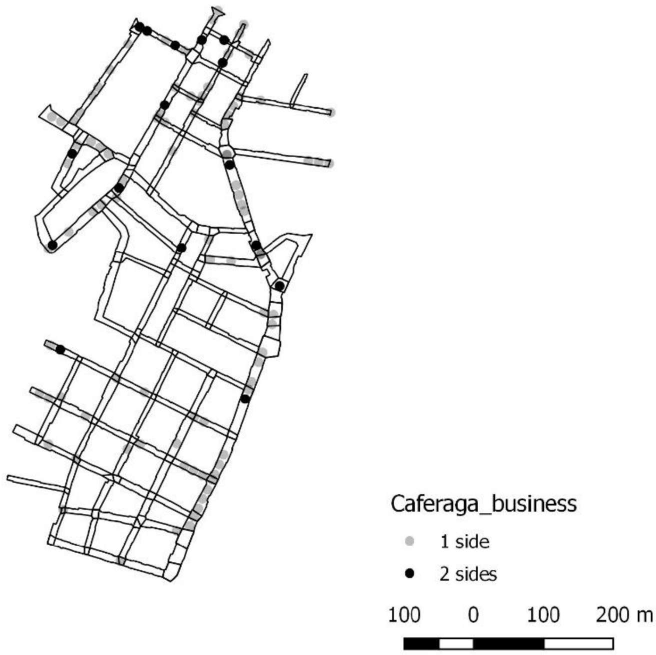


Figure G.18 : Lisbon NSS where shopping activity is identified.



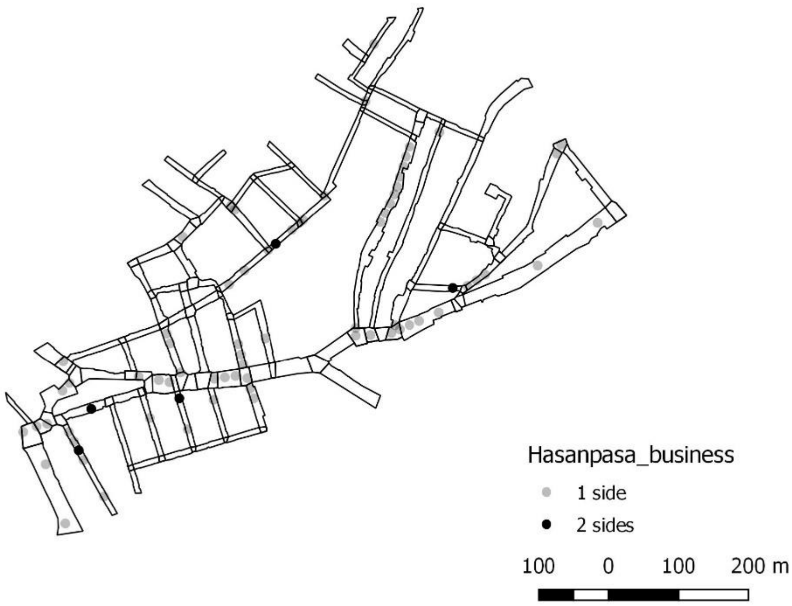


Figure G.19 : Istanbul NSS where businesses are identified.

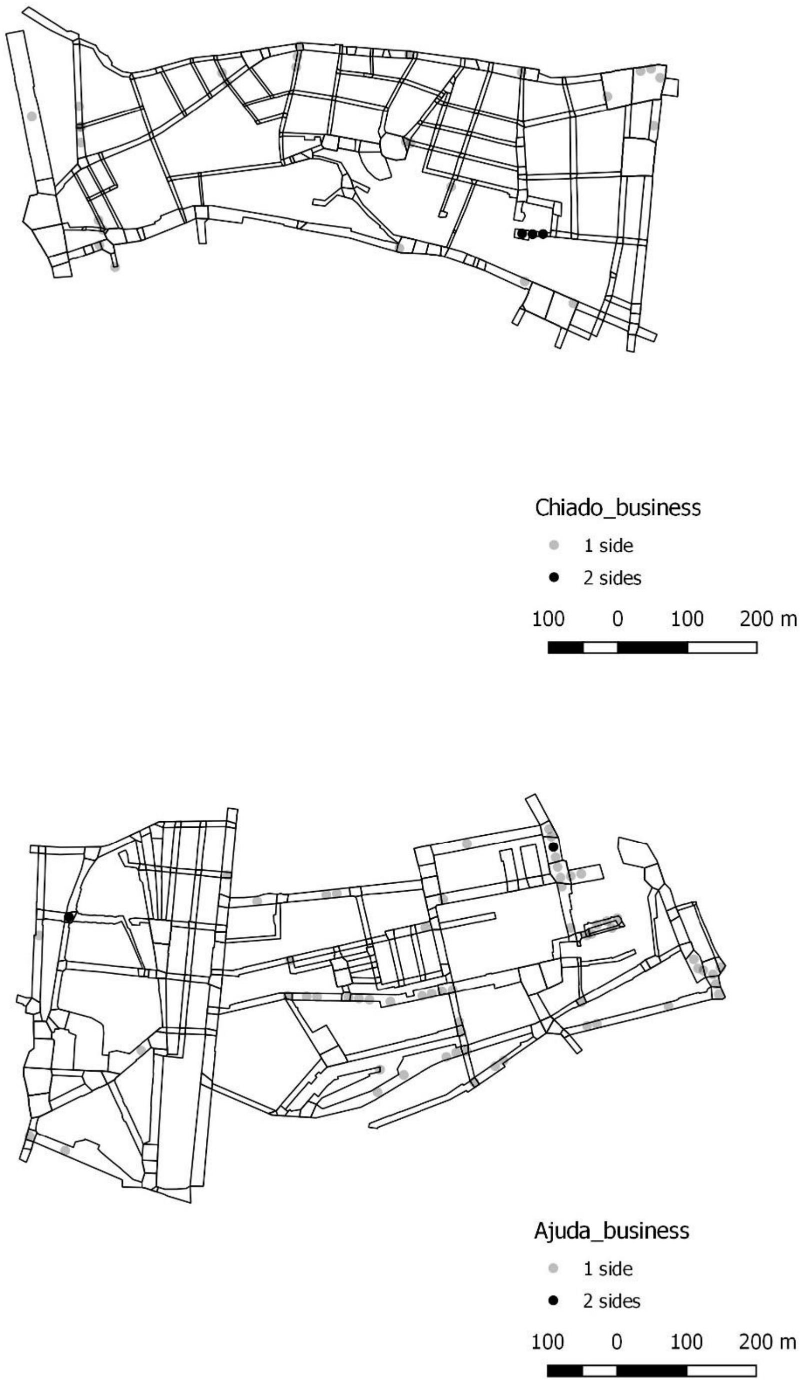
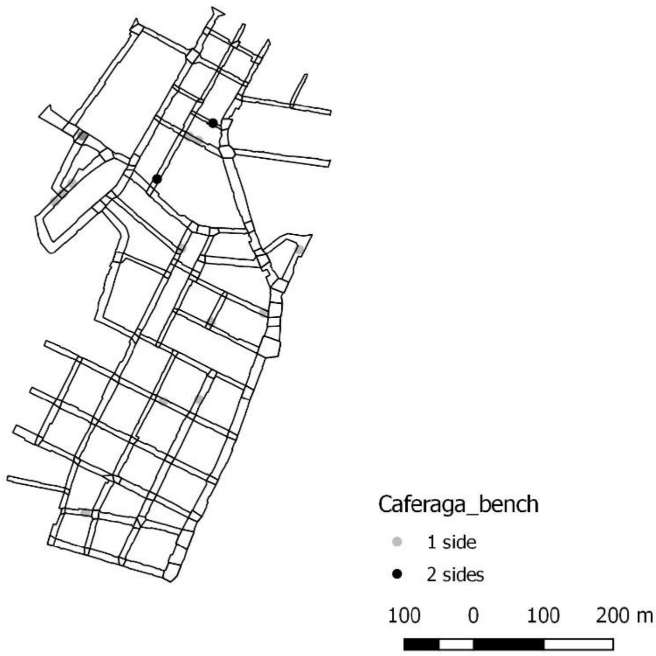


Figure G.20 : Lisbon NSS where businesses are identified.



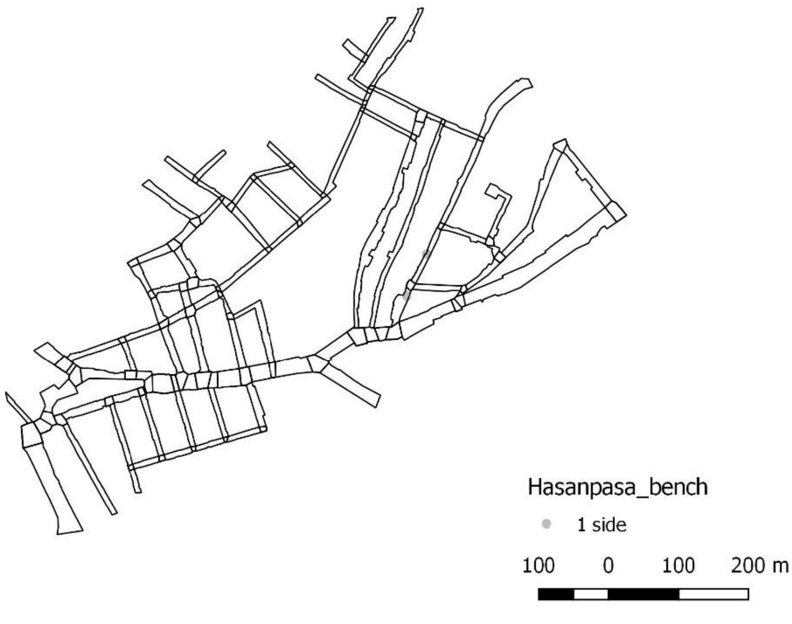


Figure G.21 : Istanbul NSS where benches are identified.

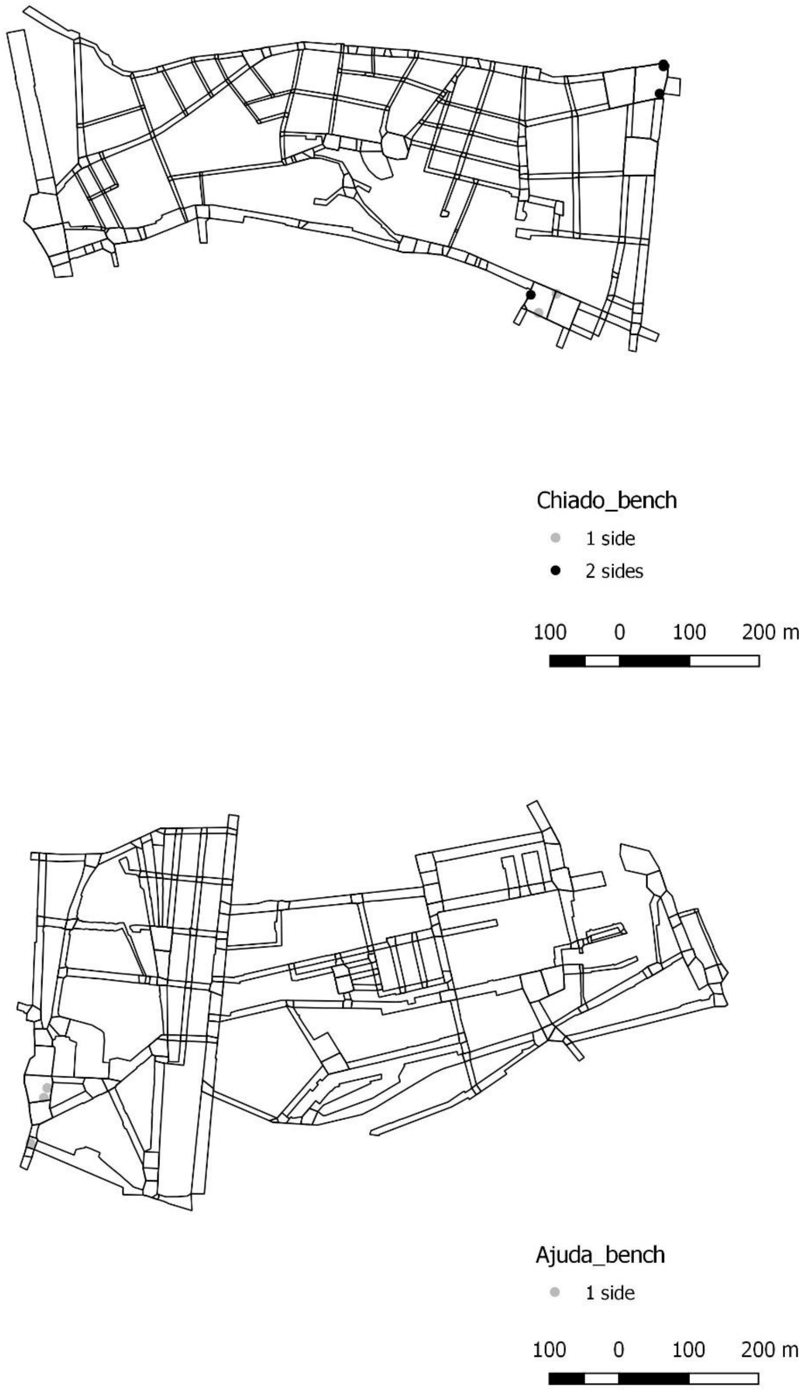


Figure G.22 : Lisbon NSS where benches are identified.

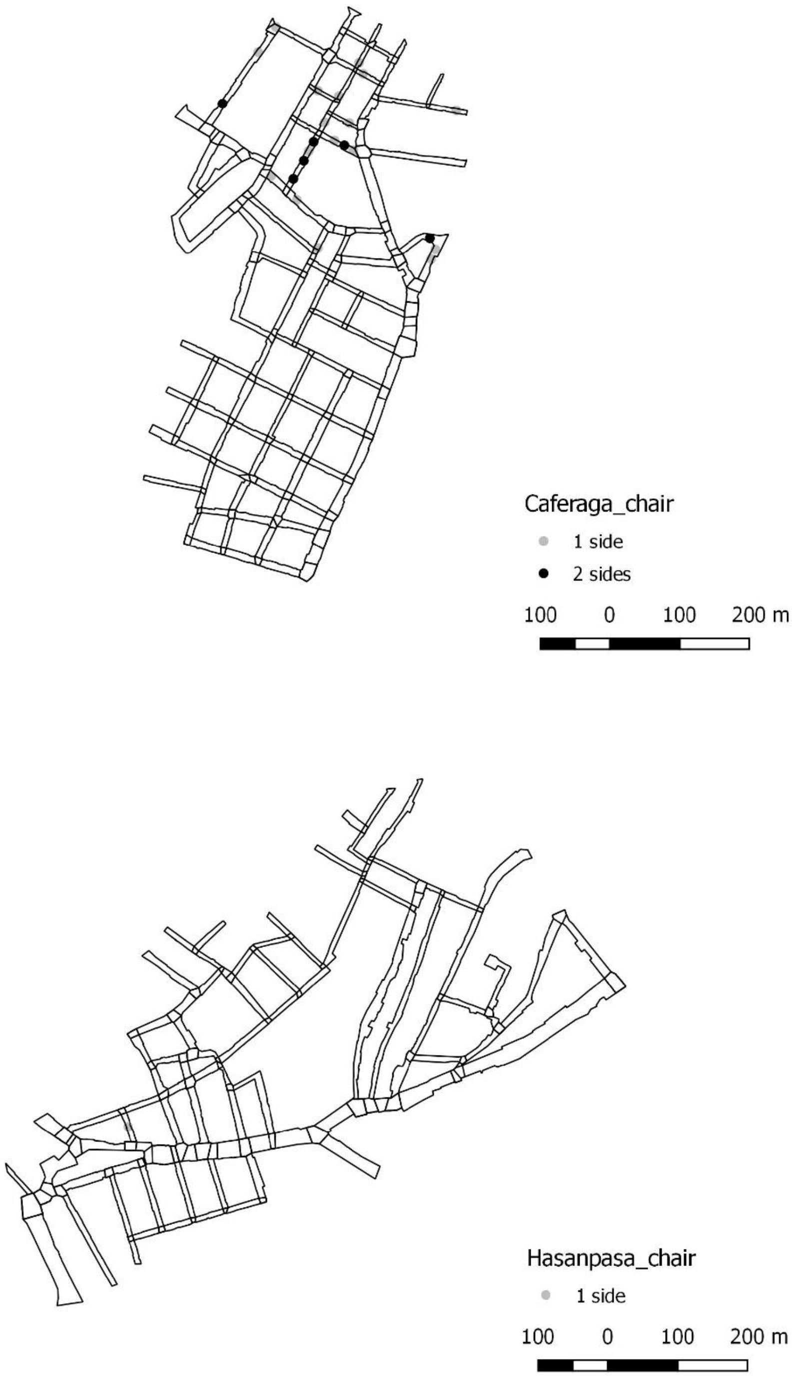
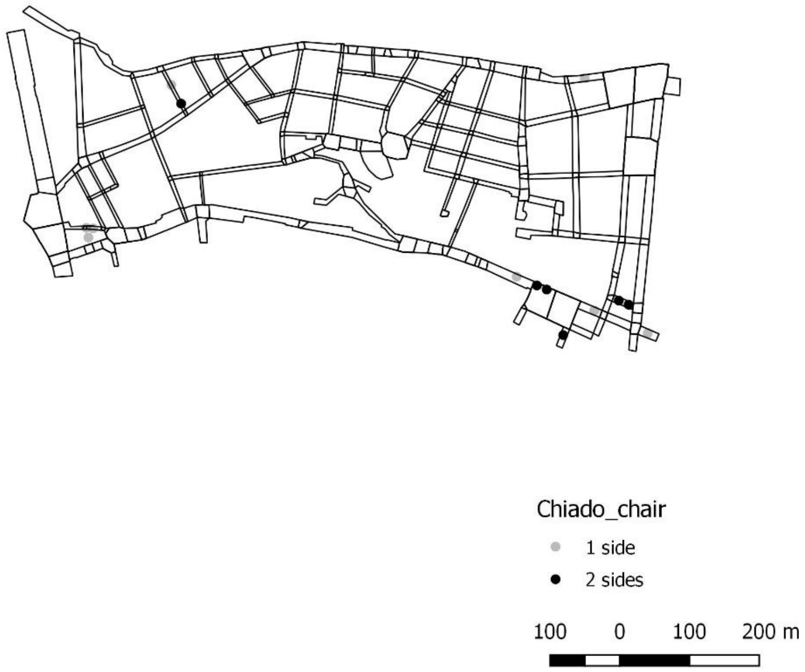


Figure G.23 : Istanbul NSS where chairs are identified.



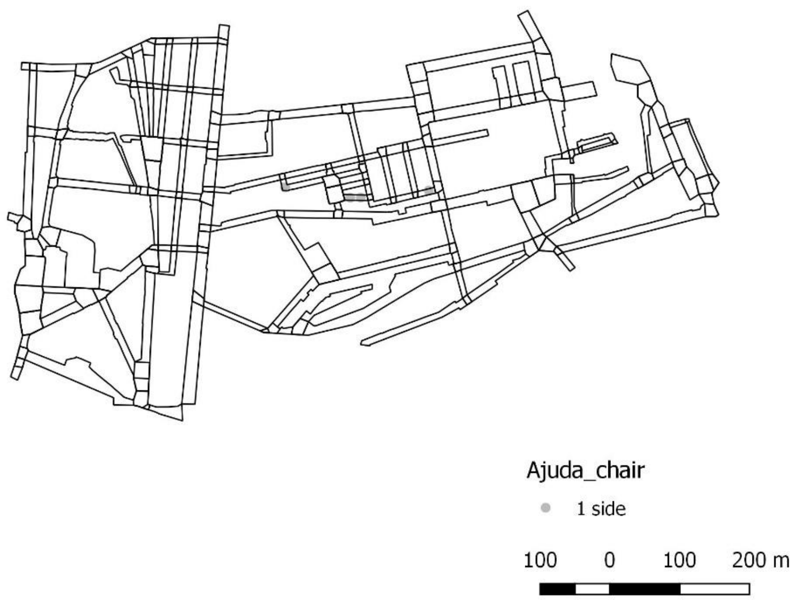
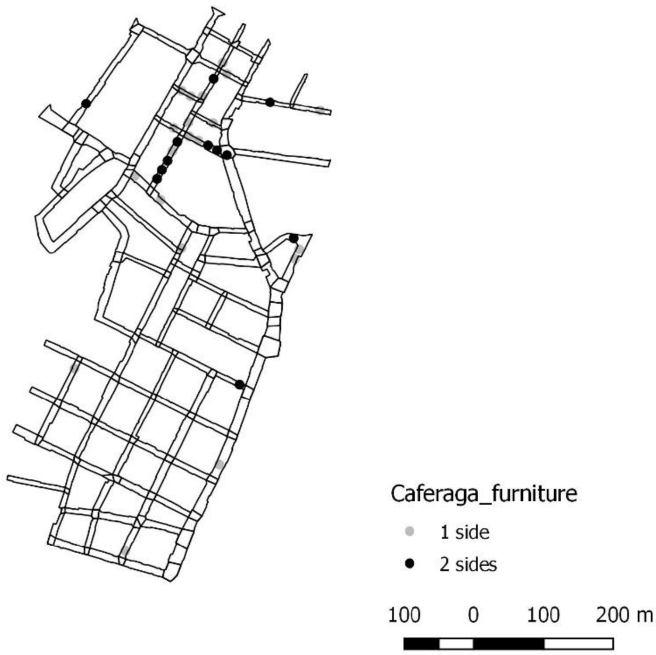


Figure G.24 : Lisbon NSS where chairs are identified.



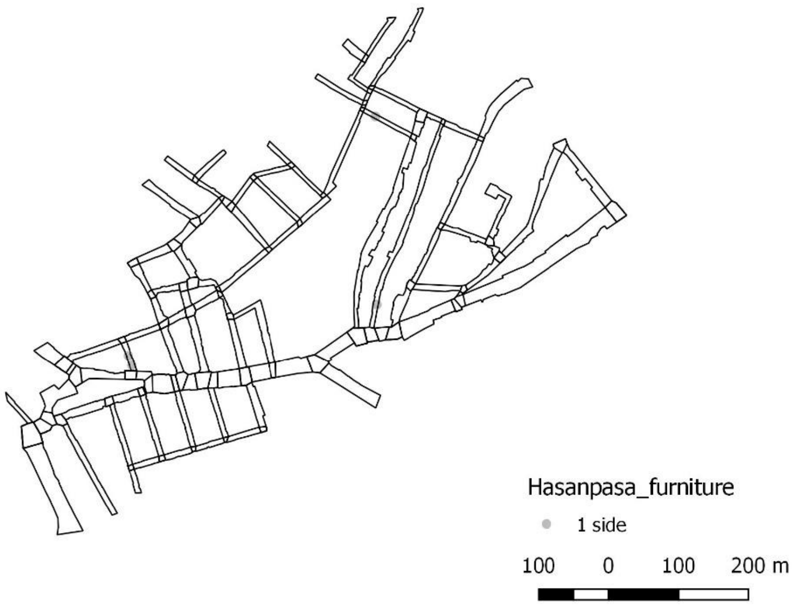
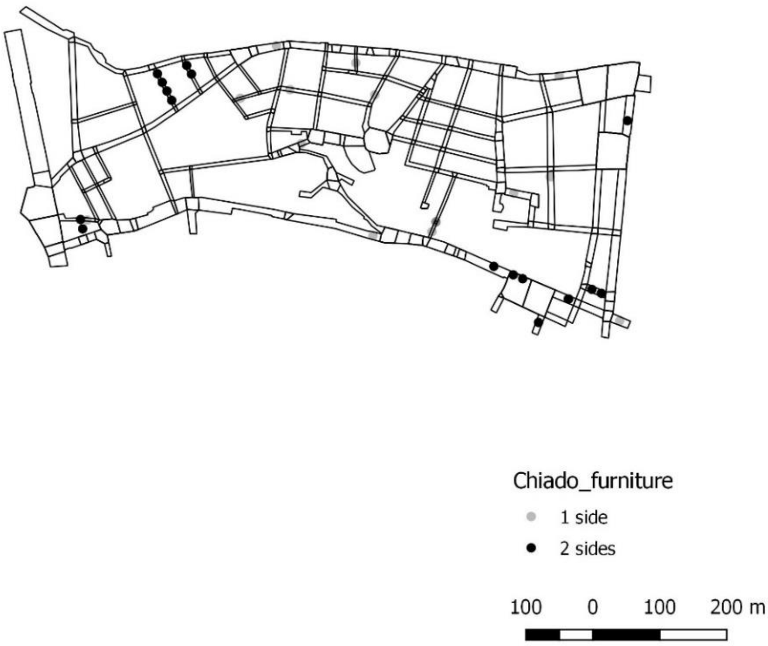


Figure G.25 : Istanbul NSS where street furniture is identified.



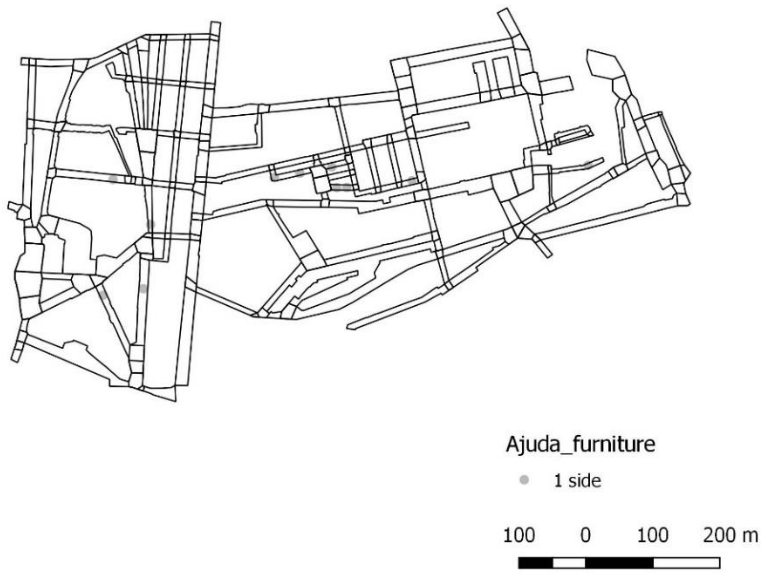
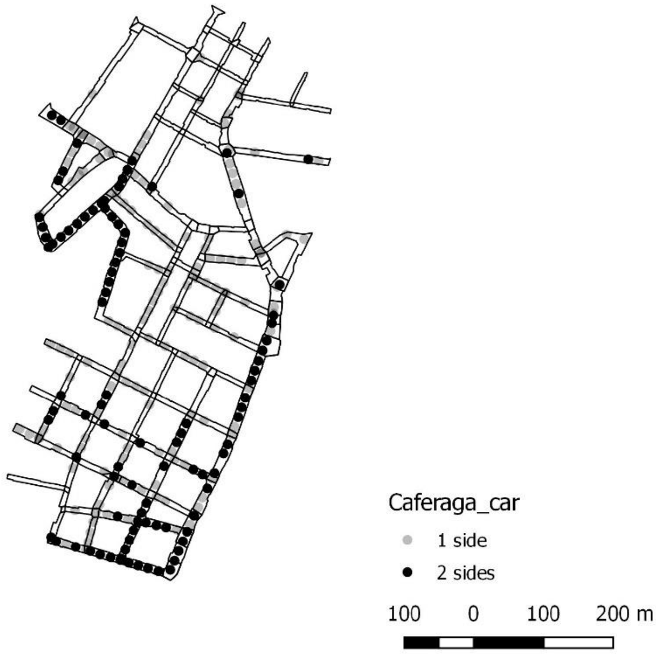


Figure G.26 : Lisbon NSS where street furniture is identified.



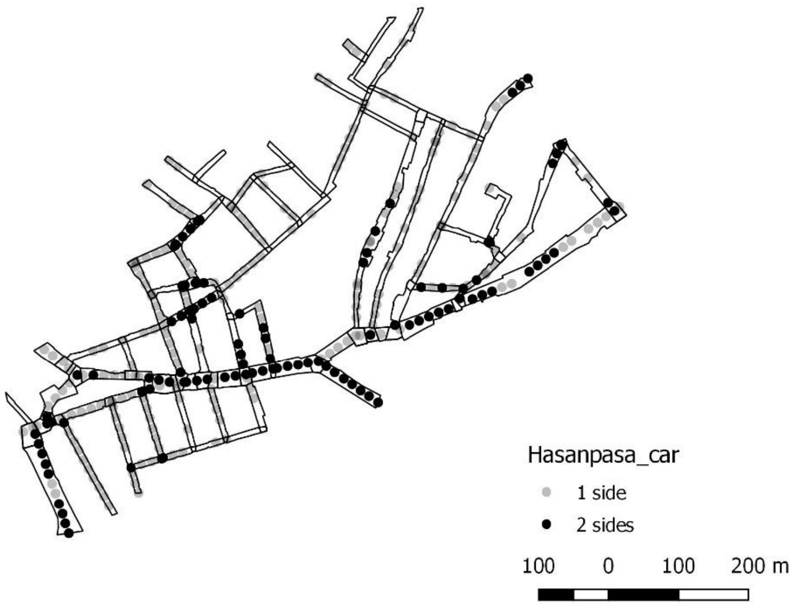


Figure G.27 : Istanbul NSS where cars are identified.

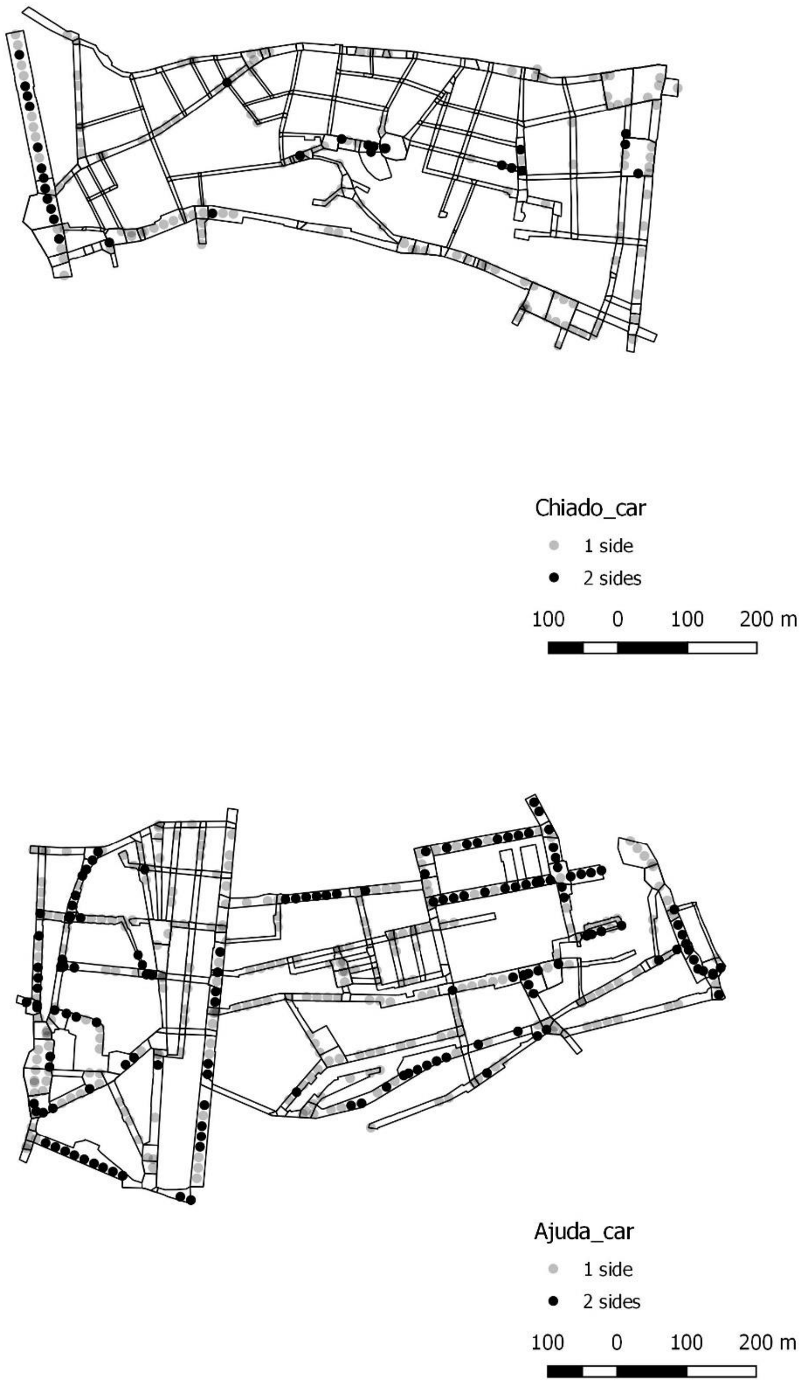
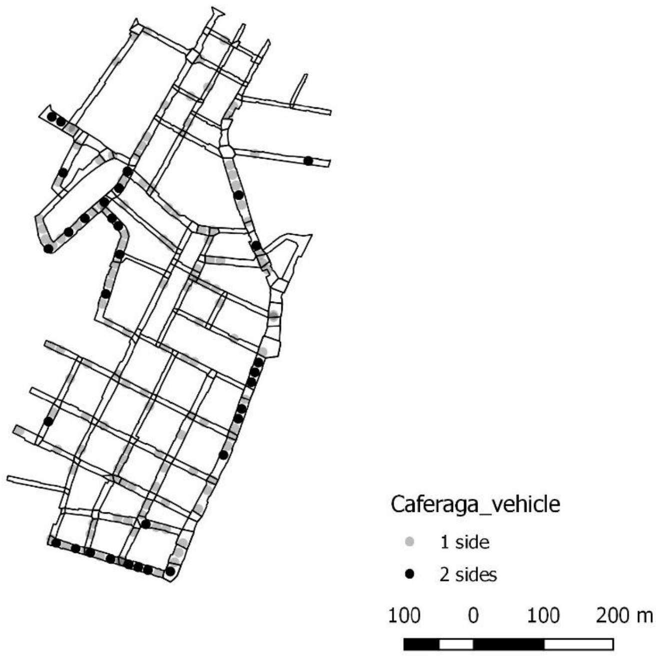


Figure G.28 : Lisbon NSS where cars are identified.



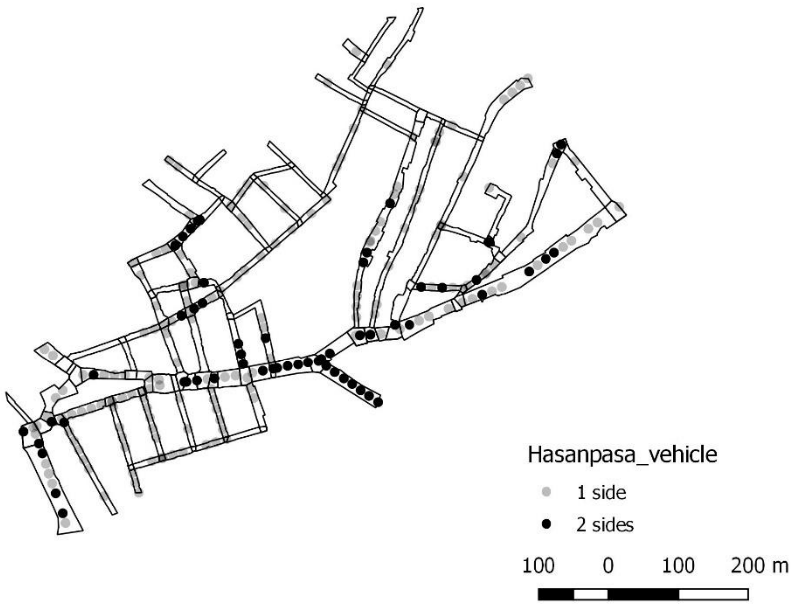
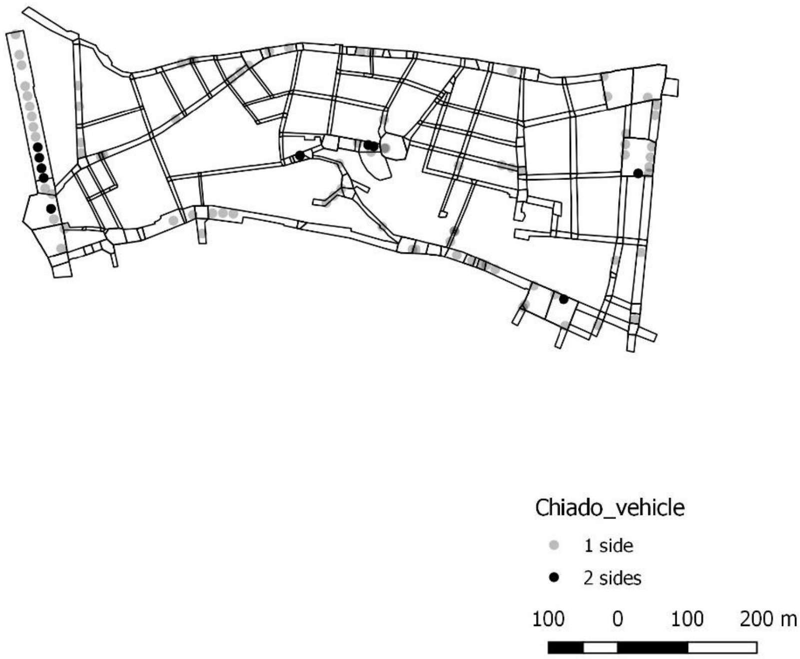


Figure G.29 : Istanbul NSS where vehicles are identified.



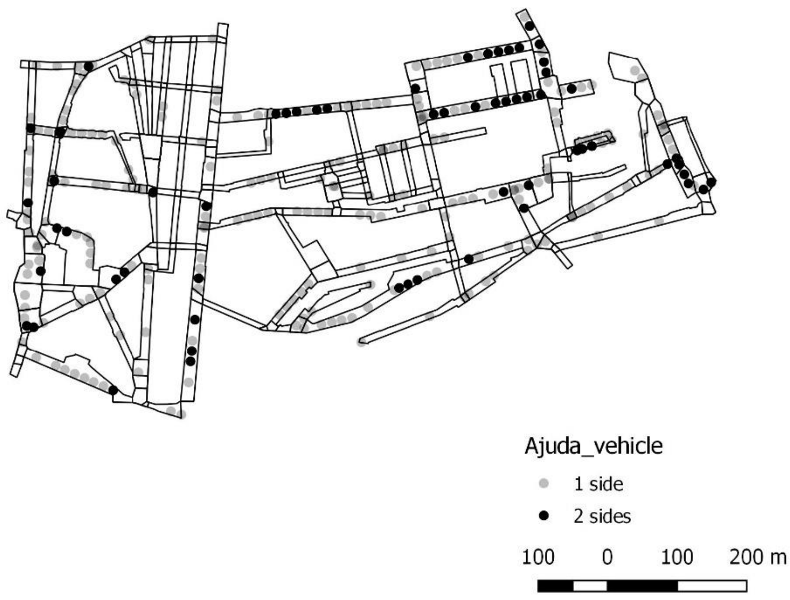
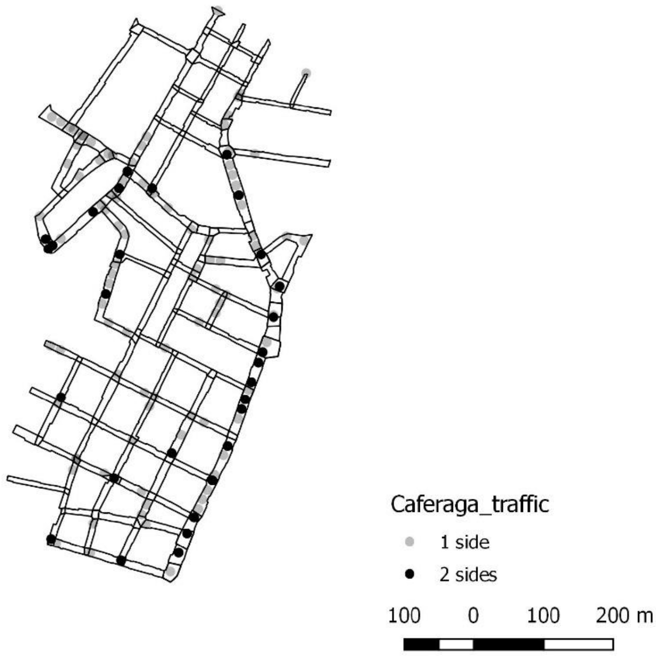


Figure G.30 : Lisbon NSS where vehicles are identified.



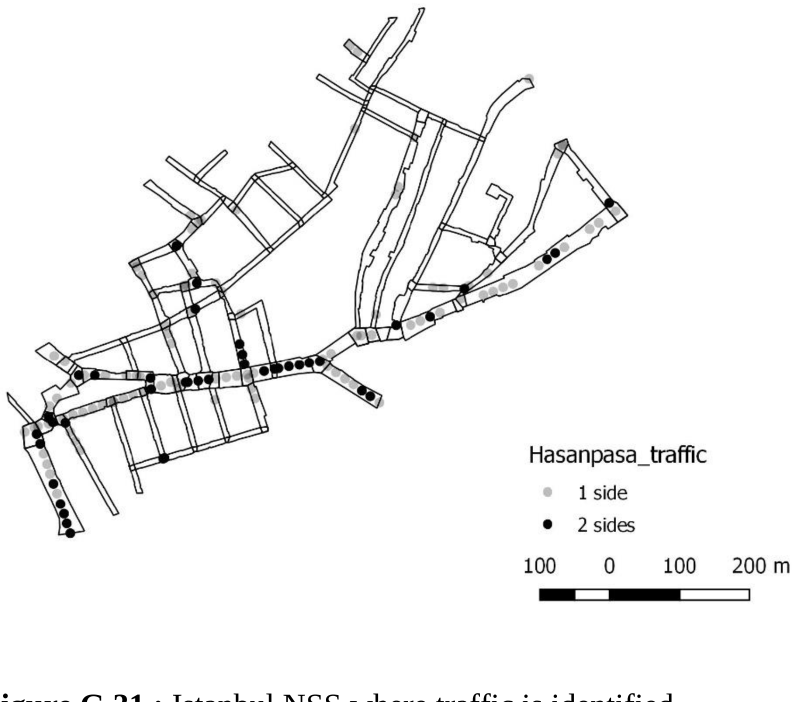
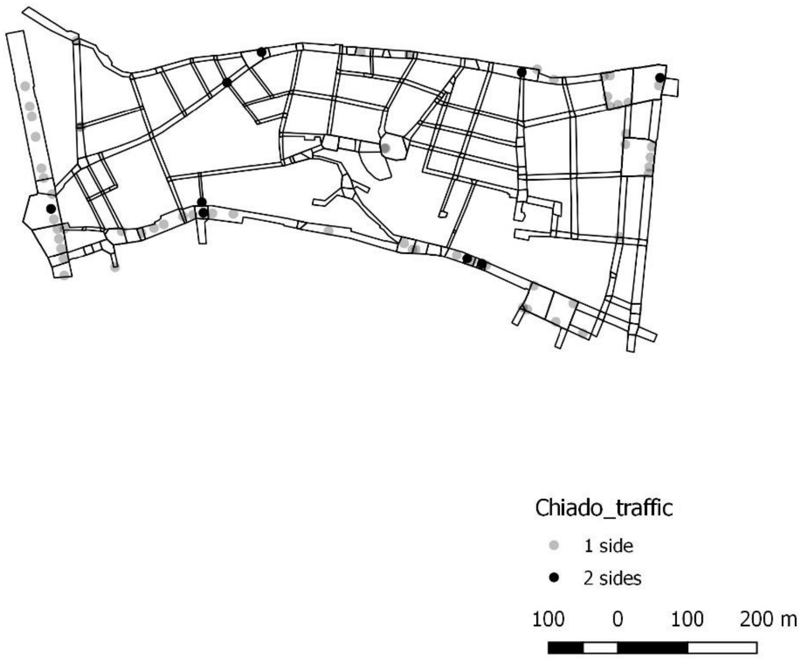


Figure G.31 : Istanbul NSS where traffic is identified.



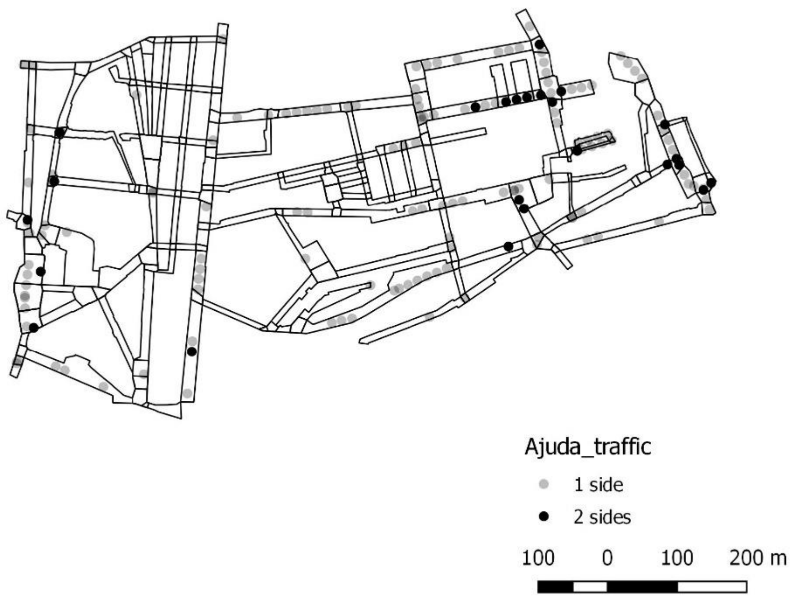
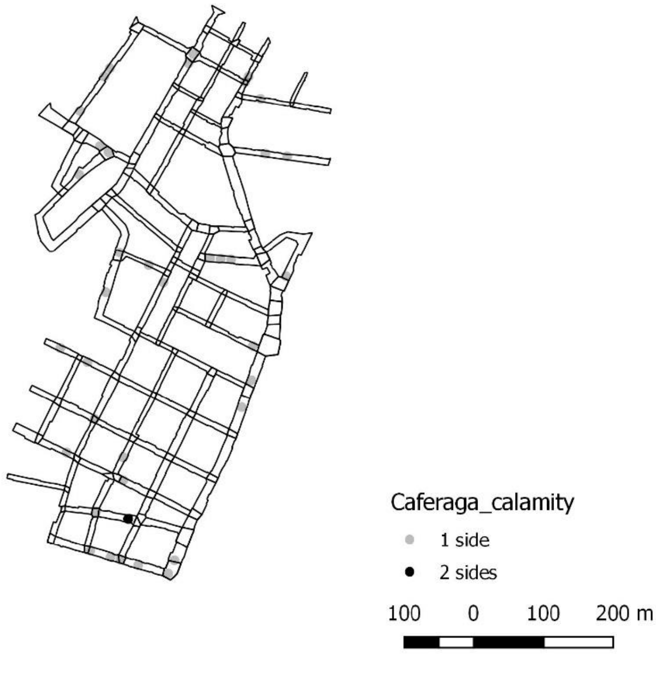


Figure G.32 : Lisbon NSS where traffic is identified.



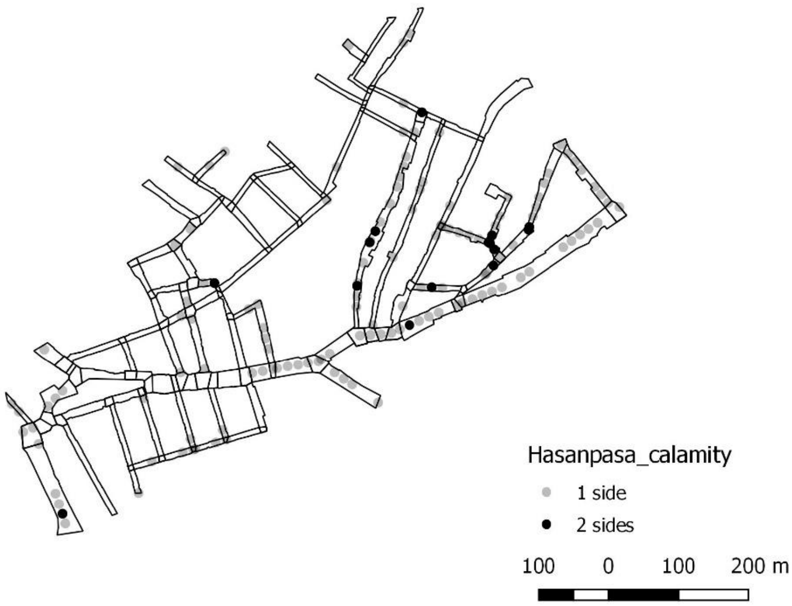
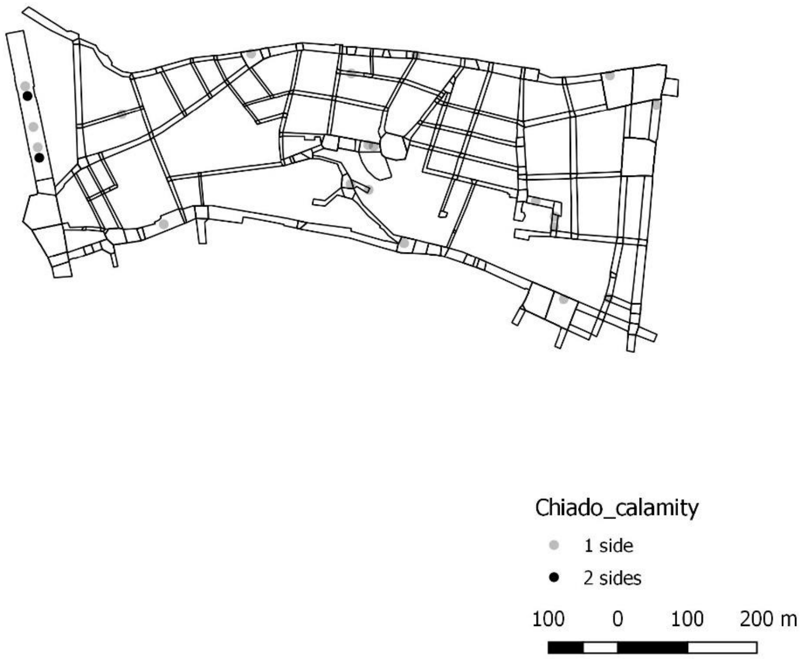


Figure G.33 : Istanbul NSS where “calamity” is identified.



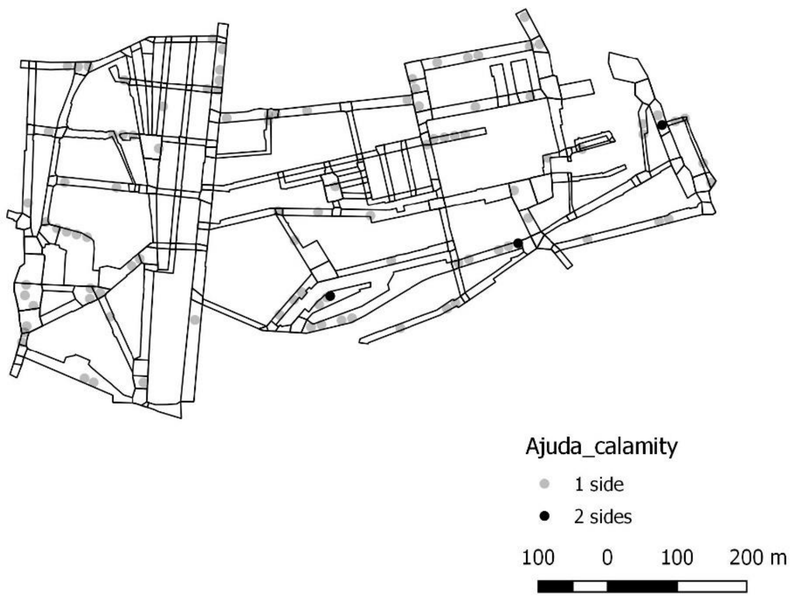
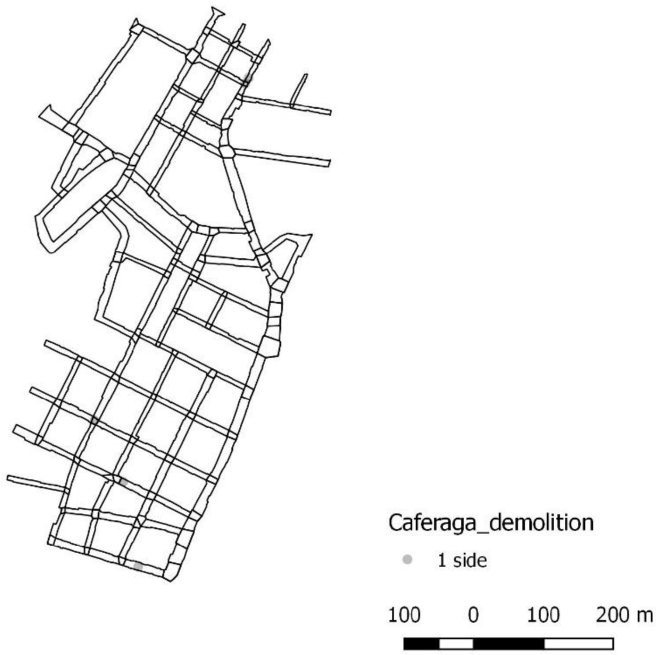


Figure G.34 : Lisbon NSS where “calamity” is identified.



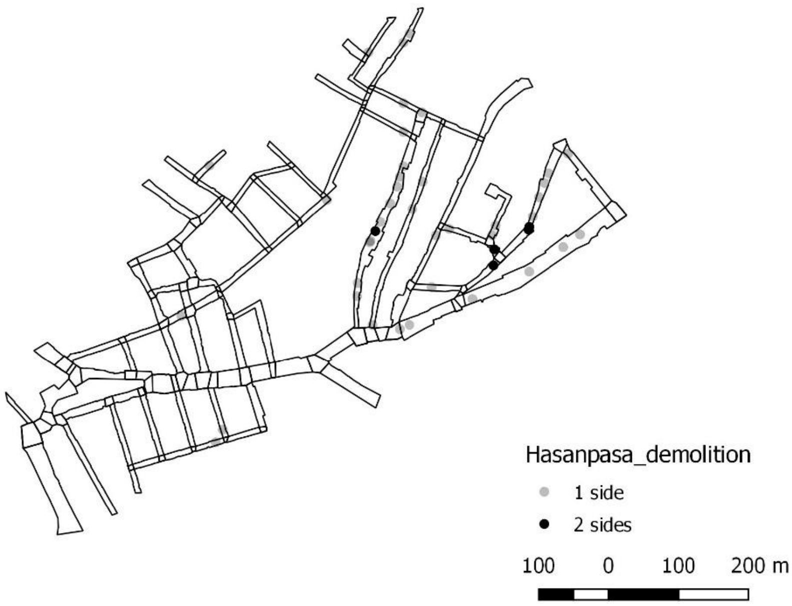
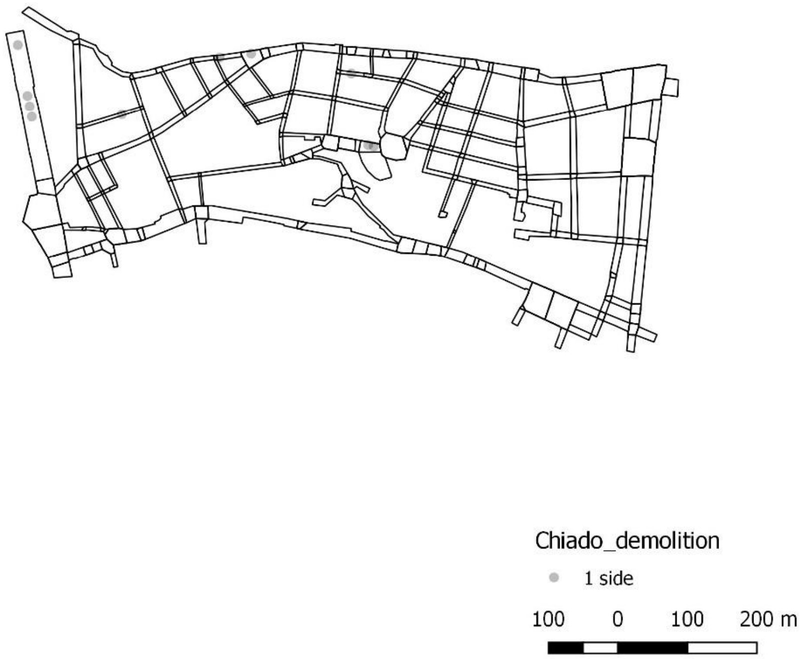


Figure G.35 : Istanbul NSS where “demolition” is identified.



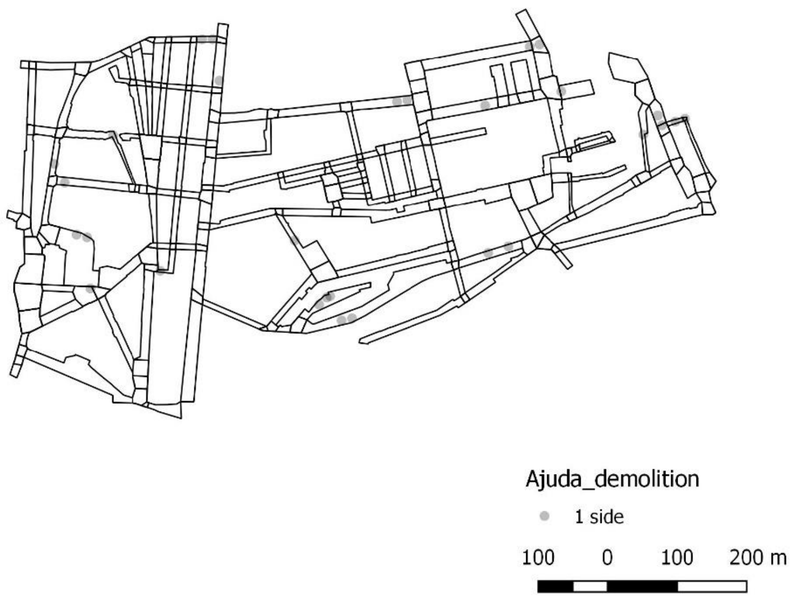
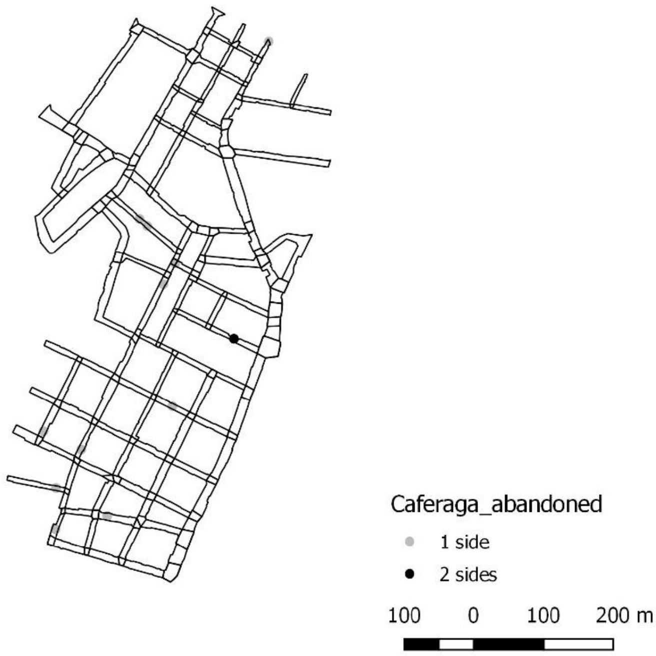


Figure G.36 : Lisbon NSS where “demolition” is identified.



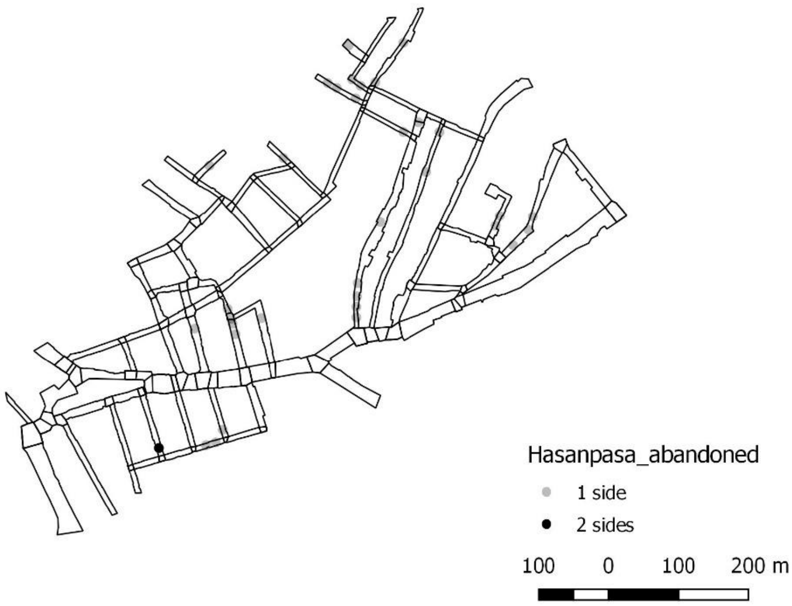
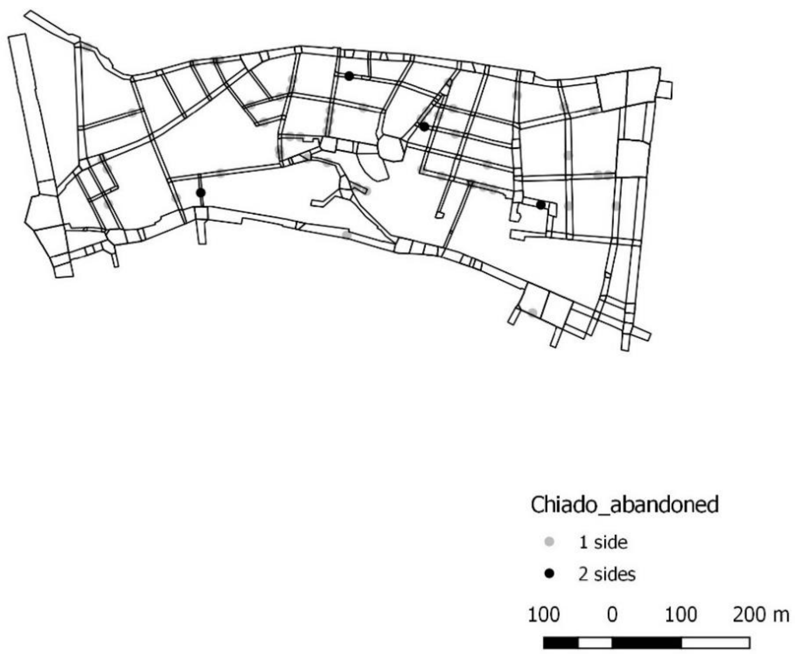


Figure G.37 : Istanbul NSS where “abandoned” tag is identified.



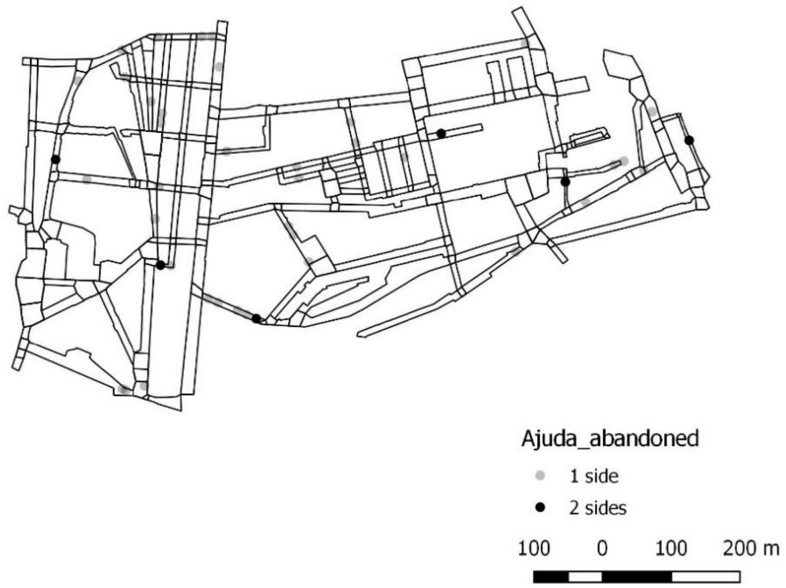


Figure G.38 : Lisbon NSS where “abandoned” tag is identified.

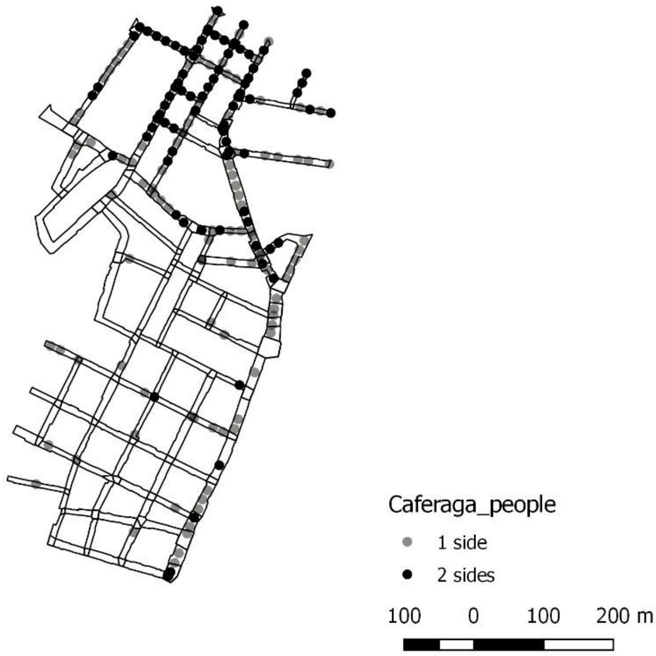
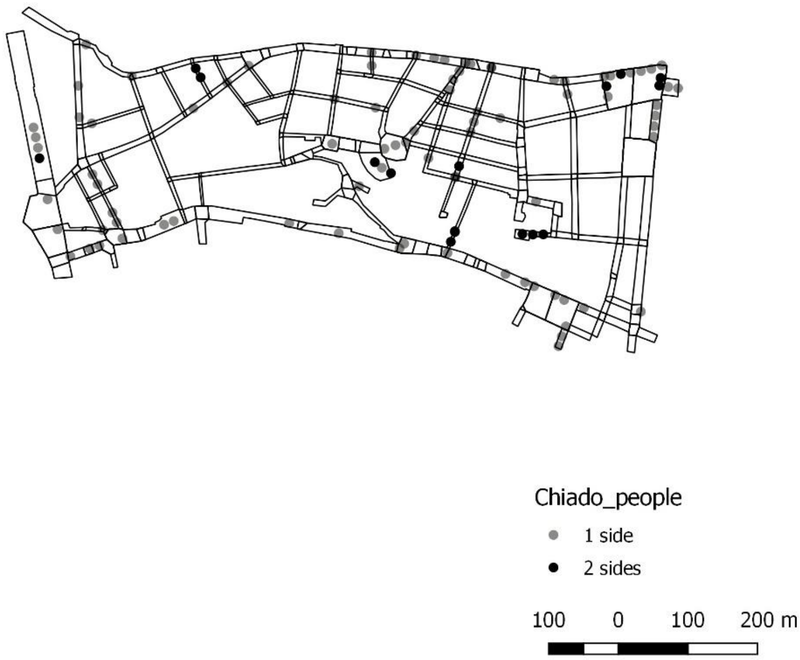


Figure G.39 : Istanbul NSS where people are identified.



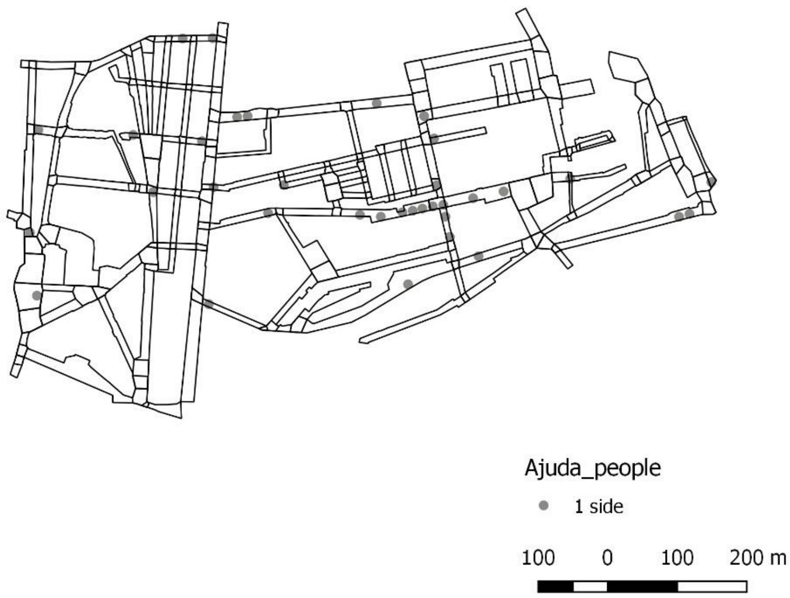


Figure G.40 : Lisbon NSS where people are identified.

APPENDIX H

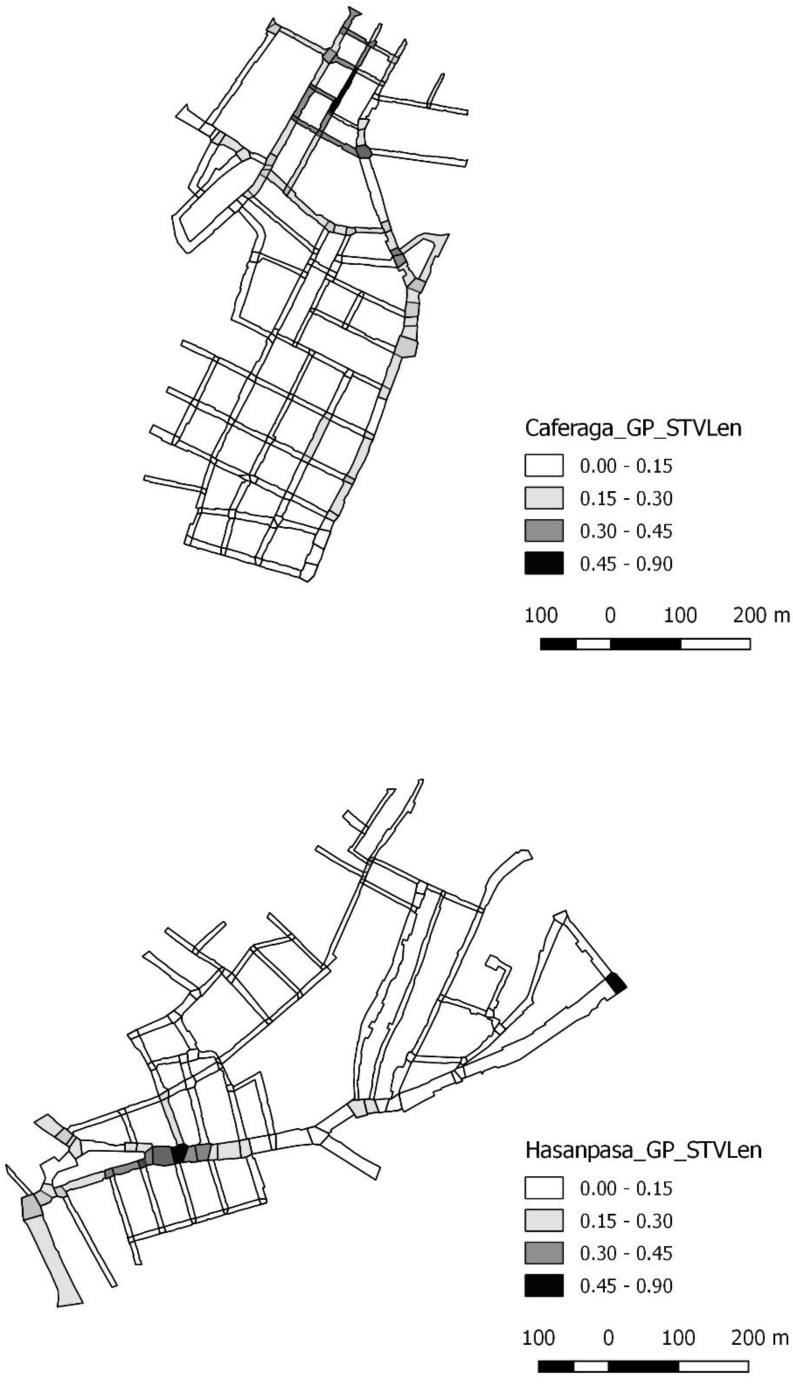


Figure H.1 : Istanbul number of Google Place locations per STV length.

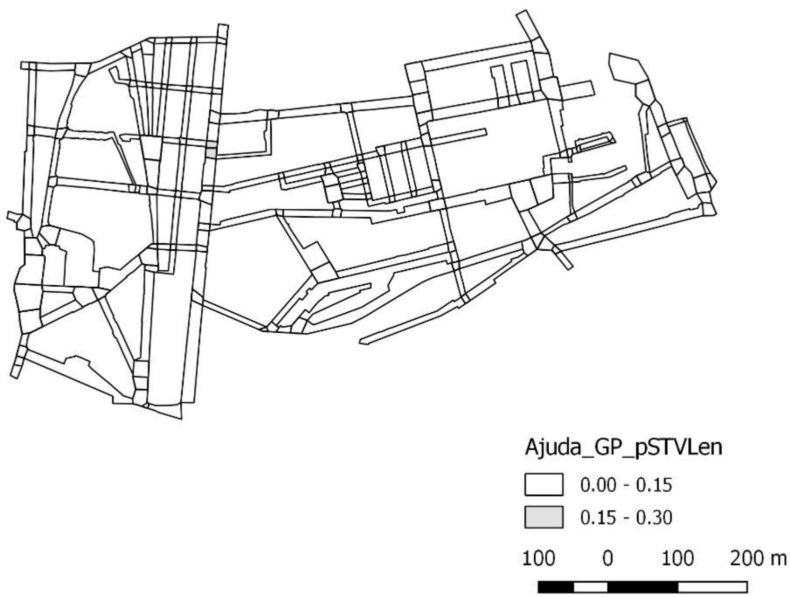
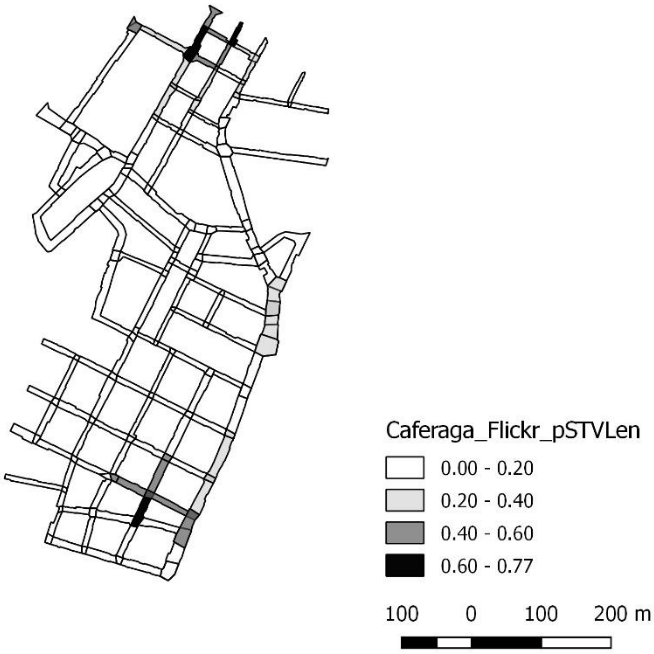


Figure H.2 : Lisbon number of Google Place locations per STV length.



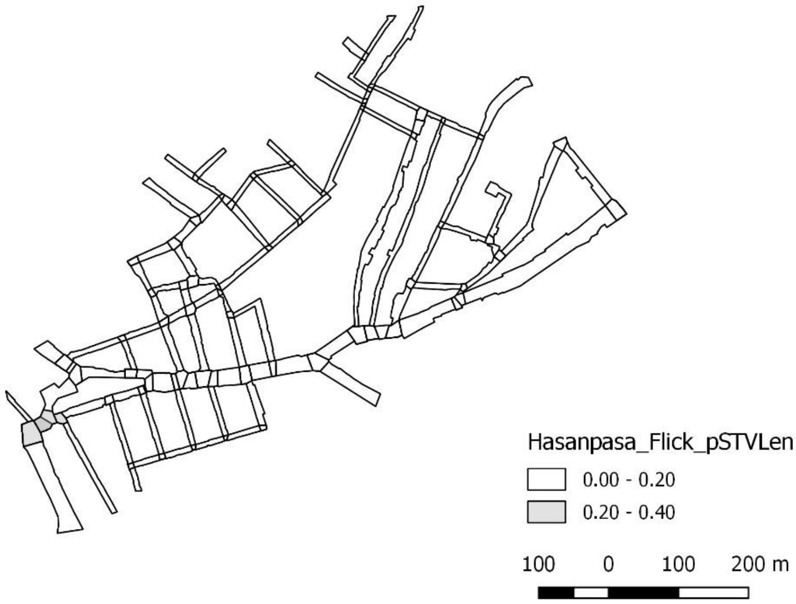


Figure H.3 : Istanbul number of Flickr posts per STV length.

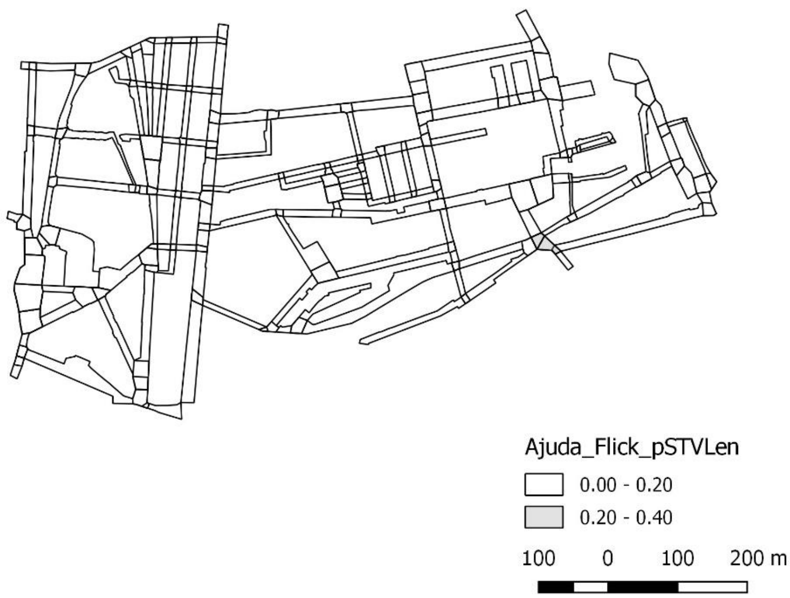
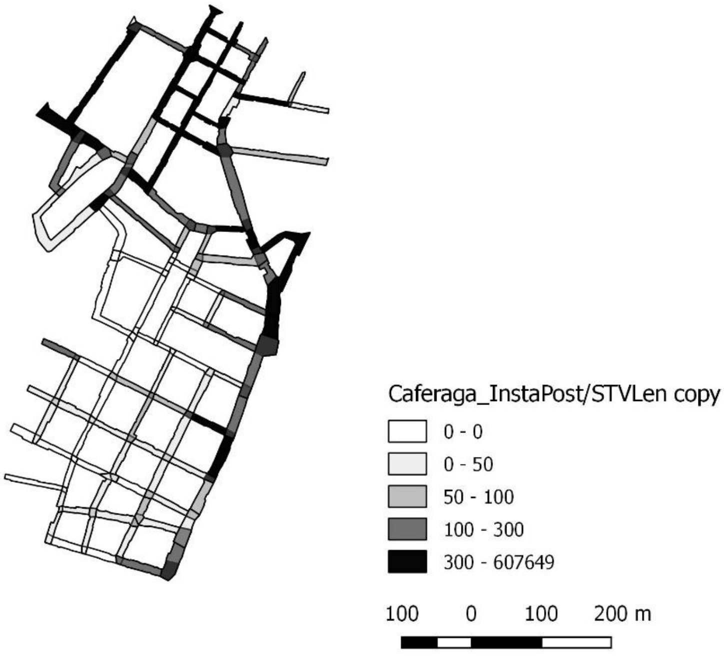


Figure H.4 : Lisbon number of Flickr posts per STV length.



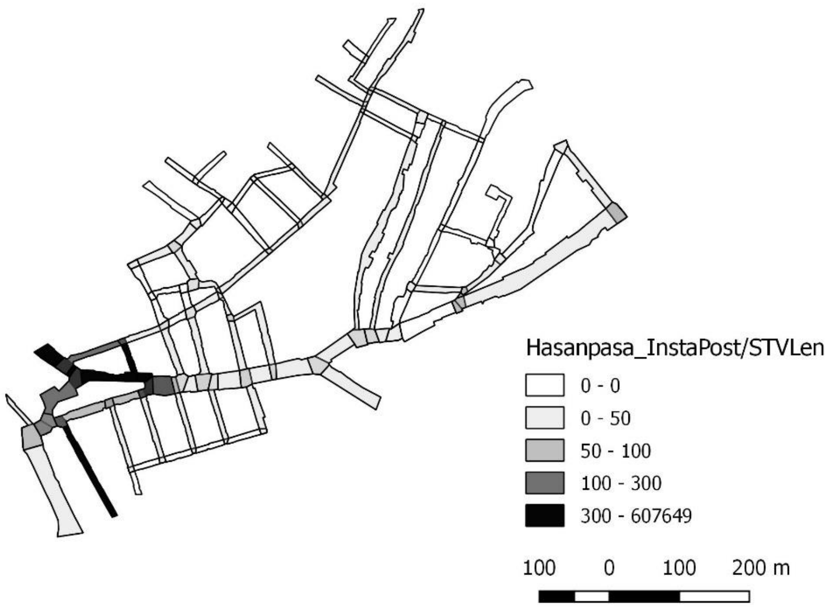
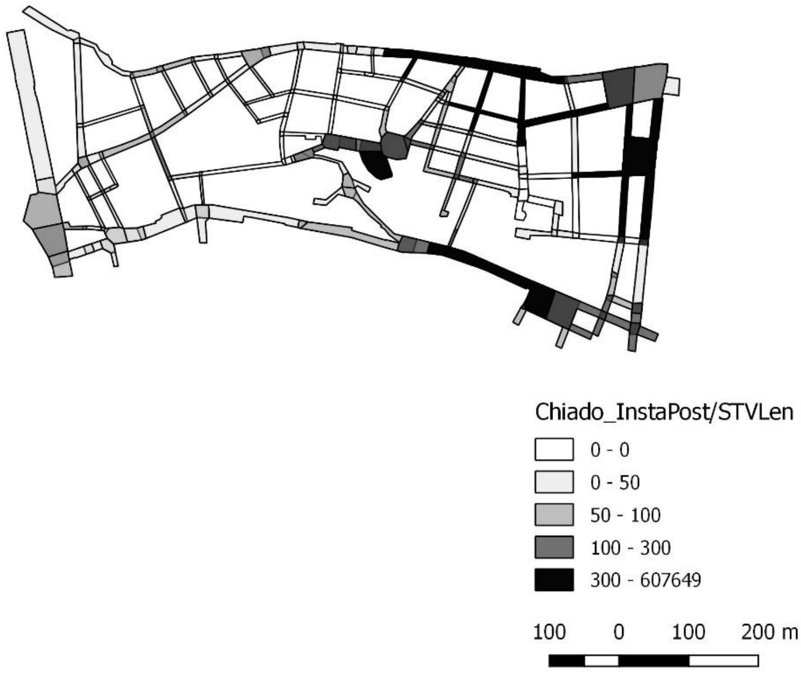


Figure H.5 : Istanbul number of Instagram posts per STV length.



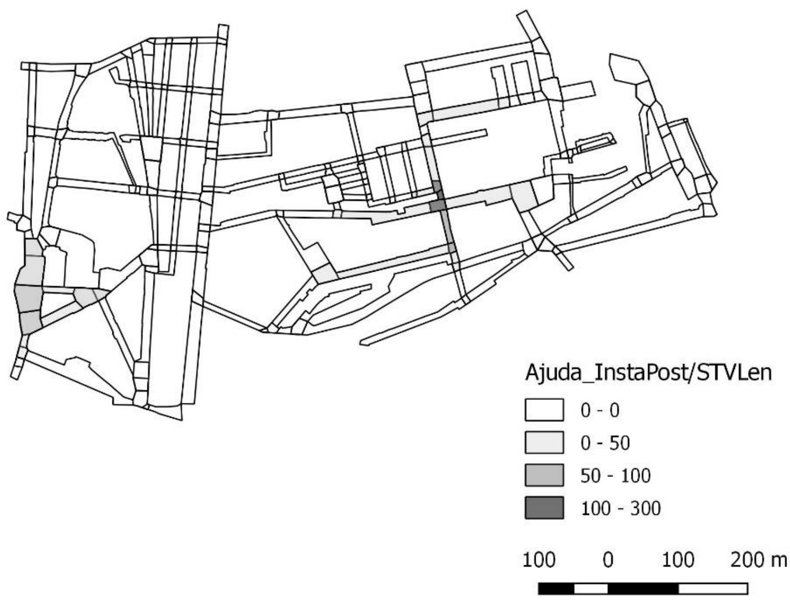
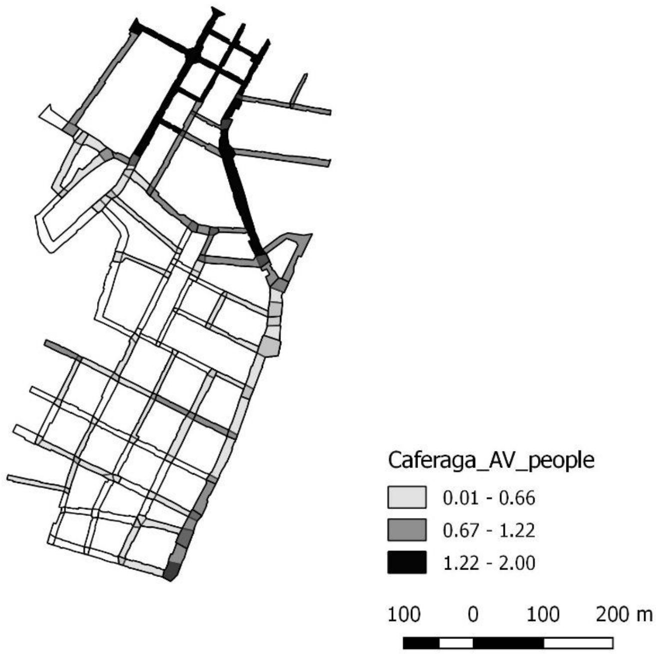


Figure H.6 : Lisbon number of Instagram posts per STV length.



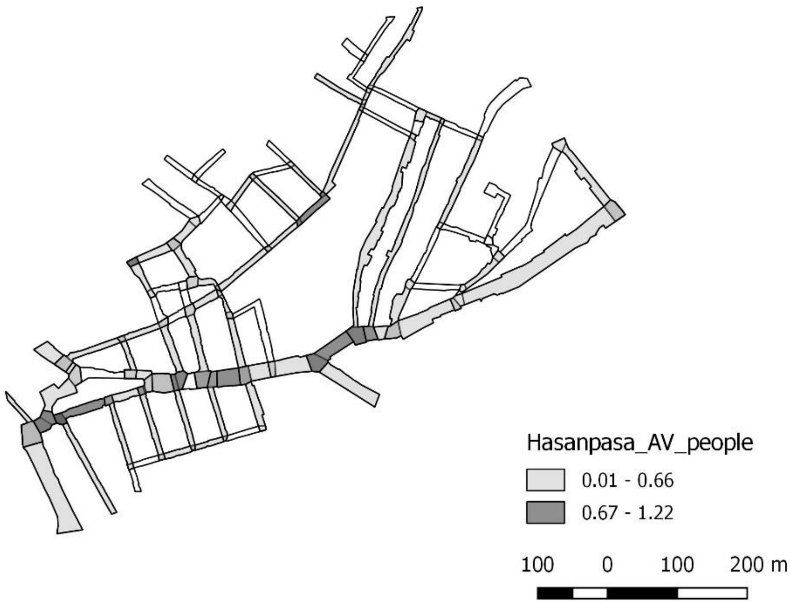
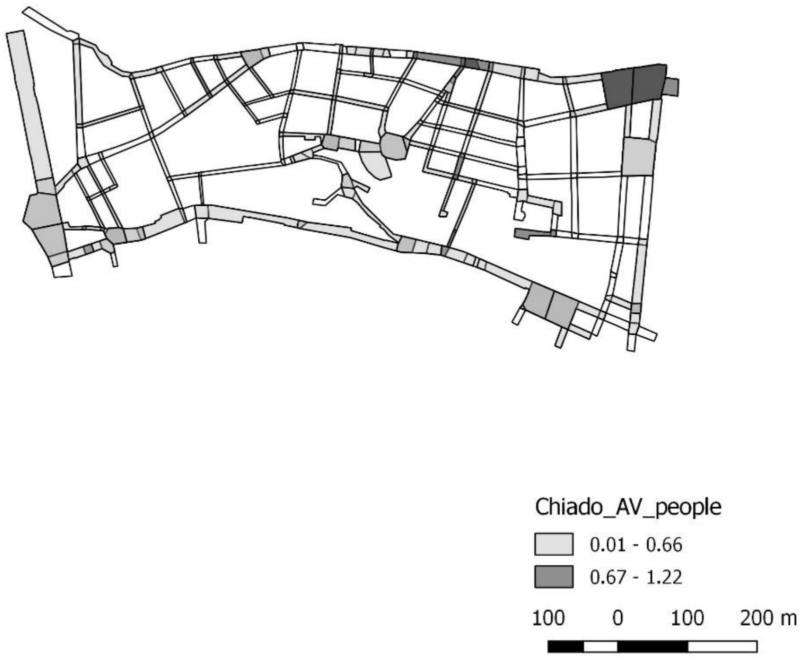


Figure H.7 : Istanbul ANSS where people are identified.



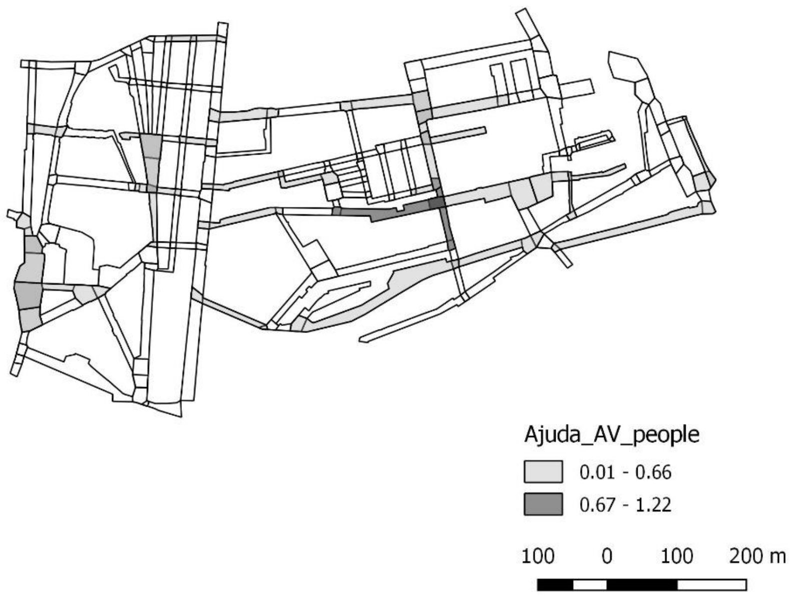


Figure H.8 : Lisbon ANSS where people are identified.